Human driver and passenger reactions to highly automated vehicles in mixed traffic on highways and in urban areas

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Contents

Abstract

In the future, highly automated vehicles (SAE Level 3 / 4) will be introduced in road traffic, first on highways, and later in urban areas. The introduction of this technology will presumably result in a long transition phase with mixed traffic. This transition phase poses new challenges for humans as passengers inside highly automated vehicles and for humans as (manual) drivers interacting with highly automated vehicles in mixed traffic. Thus far, human drivers lack experience with both highly automated vehicles and driving in mixed traffic. In addition, it can be expected that highly automated vehicles will drive in a more rule-compliant and defensive way than human drivers. This may cause conflicts with human drivers (in first contact) in mixed traffic on the one hand, and lead to passenger discomfort and feelings of risk on the other hand.

This dissertation investigated how humans react to highly automated vehicles in mixed traffic, taking both inside perspective of passengers and the outside perspective of human drivers into account. To this end, four psychological experiments were conducted whereof three were carried out in the driving simulator and one as an online video study.

From the outside perspective, this dissertation investigated human drivers' first contact with highly automated vehicles in dyadic interactions in selected driving situations on the highway (Study 1) and human drivers' repeated contact with these vehicles on longer highway sections (Study 2). Results showed that human drivers rate the rule-compliant automated driving behavior as pleasant and safe in dyadic interactions. However, human drivers feel slowed down by preceding highly automated vehicles on longer stretches of highway, which can be a potential hazard. Furthermore, an external labelling of highly automated vehicles may be recommendable in the long run.

From the inside perspective of passengers, this dissertation investigated urban mixed traffic interactions with cyclists and pedestrians in longitudinal traffic (Study 3) and at a junction (Study 4). Results show that passengers do not accept any risk during highly automated driving and passengers want an early behavioral reaction of the highly automated vehicle to vulnerable road users in the driving environment.

Across the four studies, the present dissertation shows that highly automated vehicles drive noticeably differently, which both passengers and manual drivers can perceive. However, highly automated driving behavior is perceived as unpleasant at maximum, but not as dangerous. When designing highly automated driving functions, both driver and passenger preferences should be considered equally. Future studies should further examine the preferences of (vulnerable) human road users (pedestrians, cyclists etc.) regarding automated driving behavior.

Zusammenfassung

In Zukunft werden hochautomatisierte Fahrzeuge (SAE Level 3 / 4) im Straßenverkehr eingeführt, zunächst auf der Autobahn, und später auch im urbanen Raum. Die Einführung dieser Technologie resultiert in einer voraussichtlich langen Übergangsphase mit Mischverkehr. Dieser Übergang stellt Menschen als Passagiere im hochautomatisierten Fahrzeug und als (manuelle) Fahrer vor neue Herausforderungen. Bislang fehlt menschlichen Fahrern die Erfahrung mit hochautomatisierten Fahrzeugen und dem Fahren im Mischverkehr. Zudem ist zu erwarten, dass sich hochautomatisierte Fahrzeuge regelkonformer und defensiver fahren als menschliche Fahrer. Das könnte zu Konflikten mit anderen menschlichen Verkehrsteilnehmern, und zu Diskomfort und Risikoerleben beim Passagier führen.

Diese Dissertation untersuchte mithilfe von psychologischen Experimenten im Fahrsimulator und einer Online Videostudie wie menschliche Fahrer auf hochautomatisierte Systeme aus der Passagiersicht und aus der Außensicht als manuelle Fahrer im Mischverkehr reagieren. Ein weiteres Ziel war es zu verstehen, wie hochautomatisierte Fahrzeuge fahren sollen, damit sich menschliche Passagiere möglichst sicher fühlen.

Aus der Außensicht menschlicher Fahrer untersuchte diese Dissertation den Erstkontakt mit hochautomatisierten Fahrzeugen in dyadischen Interaktionen in ausgewählten Fahrsituationen im Erstkontakt (Studie 1) und im wiederholten Kontakt (Studie 2) auf längeren Autobahnabschnitten. Die Ergebnisse zeigen, dass menschliche Fahrer das regelkonforme hochautomatisierte Fahrverhalten in dyadischen Interaktionen als angenehm und sicher bewerten. Allerdings fühlen sich menschliche Fahrer auf längeren Strecken ausgebremst, wodurch ein Gefahrenpotenzial entsteht kann. Weiterhin ist eine Außenkennzeichnung automatisierter Fahrzeuge auf längere Sicht zu empfehlen.

Aus der Innensicht menschlicher Passagiere im hochautomatisierten Fahrzeug untersuchte diese Dissertation urbane Mischverkehrsinteraktion mit Radfahrern und Fußgängern im longitudinalen Verkehr (Studie 3) und an einer Einmündung (Studie 4). Die Ergebnisse zeigen, dass Passagiere beim hochautomatisierten Fahren keinerlei Risiko eingehen wollen, und sich eine frühzeitige Verhaltensreaktion des hochautomatisierten Fahrzeugs auf schwächere Verkehrsteilnehmer in die Fahrumgebung wünschen.

Studienübergreifend zeigt sich, dass hochautomatisierte Fahrzeuge merklich anders fahren, was Passagiere als auch für manuelle Fahrer wahrnehmen können. Automatisiertes Fahrverhalten wird aber maximal als unangenehm, nicht als gefährlich bewertet. Bei der technischen Auslegung automatisierter Fahrfunktionen sollten die Präferenzen von anderen menschlichen Fahrern und Passagieren gleichermaßen berücksichtigt werden. Zukünftige Studien sollten auch die Präferenzen anderer menschlicher Verkehrsteilnehmer (Fußgänger, Radfahrer usw.) im Hinblick auf das Verhalten automatisierter Fahrzeuge weiter untersuchen.

1 Introduction

Currently, partially automated vehicles (SAE Level 2; SAE, 2014, 2018) share the road with non-automated vehicles (SAE Level 0) and assisted vehicles (SAE Level 1). In non-automated and assisted driving, the driver is responsible for both performing and monitoring the driving task and the driving environment at the same time. At the stage of semi-automated driving (SAE Level 2), the vehicle takes over the driving task, but the driver must constantly monitor the driving environment and intervene in case of system errors. As of the level of highly automated driving (SAE Level 3 or higher), former human drivers become passengers in their vehicles (Rothenbücher et al., 2016), as they can temporarily transfer the driving task to the automated system without having to monitor the automated system. At the level of conditional automation (SAE Level 3), human drivers have a hybrid function being passengers on the one hand, but serve as a fallback level on the other hand, i.e. they receive a take-over request from the highly automated system before a system limit is reached. From SAE Level 4 onwards, human drivers do not serve as a fallback level for the automated system anymore. Instead, the highly automated vehicle can transfer the vehicle into a risk-minimal state if a system limit is reached.

Highly automated driving functions (SAE Level 3) will initially be introduced on highways (Audi, 2017; Daimler, 2019; VDA, n.d.; see also Appendix A). German car manufacturers have been testing highly automated driving functions on highways (e.g., Aeberhard et al., 2015) as well as on rural roads and in urban areas (e.g., Ziegler et al., 2014) for several years now. The introduction of automated driving functions is accompanied by a number of expected benefits, including the ability for passengers to perform non-driving related tasks while driving, increased road safety, increased road capacity, reduced emissions, fuel savings and provision of mobility for impaired or older persons (Fagnant & Kockelman, 2015). The first Level 3 driving function is planned to be a traffic jam pilot by the German car manufacturer Audi AG (Audi, 2017). The traffic jam pilot takes over the driving task in congested and convoy traffic up to 60 km/h without permanent monitoring by the driver. Before a system limit of the automated driving function is reached, e.g., when a congestion resolves, the driver is requested to take over the driving task. Audi's *AI Traffic Jam Pilot* was first announced in 2017 (Audi, 2017), then postponed to 2020, and finally cancelled for the current *A8* model in April 2020 as there was no international legal framework to regulate liability during highly automated driving and the current model had already progressed too far in its model life cycle (Hetzner, 2020). Nevertheless, more car manufacturers are planning to launch highly automated driving functions for congestion as the first use-case but also beyond congested highway traffic in the near future (e.g., BMW, 2018; Daimler, 2019; Hetzner, 2020; Holzer, 2020). Assuming that automated driving functions will be introduced in the premium segment first, for example in the *Audi A8* (see Audi, 2017), it is conceivable that only a few highly automated vehicles will be travelling on the highway initially (see Kraftfahrtbundesamt, 2020d). So, it is reasonable to assume that human drivers may still be in the majority in the near future (e.g., Litman, 2021; Preuk, Stemmler, Schießl et al., 2016; see Chapter 2.2).

Approximately a decade after being introduced on highways, the introduction of highly automated driving functions in urban areas can be expected (Tabone et al., 2021; VDA, n.d.). Several project consortia have already tested highly automated passenger transport with shuttles on urban roads throughout Europe, e.g., CityMobil 2 (Alessandrini et al., 2014), EUREF (Nordhoff, et al. 2018), and the WePods project (van der Wiel, 2017).

Recently, human factors research has begun to investigate how highly automated passenger cars should interact with vulnerable road users in urban environments in various use-cases (e.g., Ackermann et al., 2019; Beggiato et al., 2018; Fritz, 2020; Fuest et al., 2018, 2019; Mayerhofer et al., 2020; Stange et al., submitted; see also Tabone et al., 2021). Moreover, a research consortium (L3 Pilot Project, 2017 – 2021) has conducted a large-scale testing of highly automated passenger cars (SAE Levels 3 & 4; SAE, 2014, 2018) on public roads across Europe to examine how safe and efficient automated driving functions are in real-world traffic (L3 Pilot Project Consortium, n.d.).

From a technology-driven perspective, the development and programming of highly automated passenger cars in urban areas is a greater challenge compared to the highway environment, as there is no structural separation of driving directions, the traffic flow is less uniform, and the traffic and obstruction densities may be higher (Campbell et al., 2010). Furthermore, the infrastructure in urban areas is complex and variable in its layout, resulting in complex interactions between highly automated vehicles and (vulnerable) human road users including pedestrians and cyclists (Ackermann et al., 2019; Campbell et al., 2010; Hubmann et al., 2016; Lee et al., 2020). In particular, pedestrian movement is very difficult to predict for highly automated driving functions beyond short-term predictions (Völz, 2020), as there is very little rule regulation or environment constraints regarding pedestrian behavior (Cambon de Lavalette et al., 2009). In addition, visual obstruction presents an additional challenge for highly automated driving functions in densely constructed urban areas (Campbell et al., 2010; Nolte et al., 2018; Völz, 2020). For example, pedestrians can suddenly and unexpectedly step onto the road from behind a parking car on a parking stand right in front of an automated vehicle (see Nolte et al., 2018). According to experts, Level 4 passenger cars will presumably be first available in urban areas around the year 2030 or even much later (see Tabone et al., 2021 for a review; VDA, n.d.), and their introduction may contribute to increase efficiency and road safety by reducing the number of crashes caused by driver error (Fagnant & Kockelman, 2015). Nevertheless, (automated) driving remains a trade-off decision between mobility and risk (Campbell et al., 2010; Nolte et al., 2018). Following from this trade-off, it is reasonable to assume that maximizing road safety would result in the overall transport system losing its efficiency as highly automated vehicles would have to drive very slowly then to achieve a maximum amount of safety for passengers inside the vehicle and for surrounding human road users. At the same time, it is reasonable to assume that driving with minimal speed would not be in the interest of passengers using highly automated vehicles as a means of transport to reach their destination of travel safely within a reasonable amount of time (e.g., Cnossen, 2000; Fuller, 1984; Summala, 2007). Essentially, one of the key questions is: What amount of risk are passengers willing to accept during automated driving? (Nolte et al., 2018; see also Fuller, 1984). Therefore, this dissertation also aims at contributing to the psychological question to what extent passengers inside highly automated vehicles attempt to avoid risk or aim at achieving an accepted level of risk, taking up the fundamental, ongoing discussion regarding psychological risk in traffic psychology (see Fuller, 2000, 2005, 2011; Nätäänen & Summala, 1974, 1976; Summala, 1988, 2007; Wilde, 1982). Until highly automated passenger cars will be introduced in urban areas, however, there is still some time to adapt the design of automated driving functions to meet passenger needs in terms of safety and efficiency.

Beyond the introductory phase of highly automated vehicles on public roads, it is difficult to estimate how the penetration rate of highly automated vehicles in road traffic will develop over the next few years (Bansal & Kockelman, 2017). As most experts agree, there will be a long transition phase of at least 30 to 40 years or even longer with *mixed traffic*, i.e. human drivers and automated vehicles sharing the road (e.g., Litman, 2021; van Loon & Martens, 2015; Zmud et al., 2019). In this dissertation, the term mixed traffic is used to describe the state where non-automated human road users (up to Level 2; SAE, 2018) and highly automated systems (Level 3 or higher; SAE, 2018) share space in road traffic. In this context, researchers have argued that a state of full automation in all vehicles may never be reached, so automation may never replace human drivers completely (e.g., Eliot, 2019; van Loon & Martens, 2015; Zmud et al., 2019).

In mixed traffic, previous interactions between human road users gradually become human-machine interactions, forming an interaction triad between human road users, automated vehicles and its passengers (Schieben et al., 2019). In this context, Markkula et al. (2020, p. 10) defined an *interaction* as “a situation where the behaviour of at least two road users can be interpreted as being influenced by the possibility that they are both intending to occupy the same region of space at the same time in the near future”. The focus of this general definition is less on actual, objective collision risks in safety-relevant situations, but more generally on the coordination of a commonly shared traffic space between road users, i.e. “space-sharing conflicts” (Markkula et al., 2020, p. 9). In order to solve a space-sharing conflict successfully, highly automated vehicles must react to human drivers’ behavior in an appropriate way and vice versa (see Markkula et al., 2020 for a taxonomy of interactive behaviors in space-sharing conflicts). Such appropriate reactions require some form of mutual understanding between humans and automated systems, which van Loon and Martens (2015) described as *compatibility issues*. The achievement of compatibility in mixed traffic may be challenging because human behavior is difficult to anticipate for automated systems (see e.g., Campbell et al., 2010; Völz, 2020), and, in turn, it can be assumed that highly automated systems may behave differently than human drivers in a number of driving situations (Fuest et al., 2020; van Loon & Martens, 2015; see Appendix A). So, if human drivers expect human-like driving behavior from an automated vehicle, this expectation might be violated (van Loon & Martens, 2015). This raises the psychological question of the role of correct expectations and mental models in interaction with highly automated vehicles in mixed traffic. Due to human drivers' lack of experience with highly automated vehicles and driving in mixed traffic, it is reasonable to assume that human drivers may initially lack suitable mental models, schemata and scripts for mixed traffic interactions (see Endsley, 1995a). In turn, highly automated vehicles can be expected to lack an understanding of human road users' social, (in)formal rules which forms the basis of interaction in human road traffic (Hancock, 2020). So, one may expect safety issues at first contact due the lack of a mutual understanding (Nyholm & Smids, 2020; van Loon & Martens, 2015) as human drivers will have to develop new mental models suitable to driving in mixed traffic which is a longer process (Endsley, 1995a; Noy et al., 2018; see also Holland et al., 1986). However, it is yet unclear whether (more or less) large deviations from human drivers' expectations and implicit knowledge must inevitably result in negative or safety-critical mixed traffic interactions (Hancock, 2018, 2020).

So, the introduction of highly automated vehicles and the resulting intermediate stage of mixed traffic may present human drivers with the new challenge to interact with a new technology that human drivers have no experience with yet. Thus, the introduction of highly automated systems places completely new demands on humans as drivers in mixed traffic. This is especially relevant for the highway environment where highly automated driving functions may be introduced soon (Audi, 2017; BMW, 2018; Daimler, 2019; VDA, n.d.). Analogously, similar challenges may arise on the part of passengers using this new technology because humans are used to be passengers being driven by other humans, but not by an automated system. Again, this places new demands on humans as passengers in mixed traffic. It is reasonable to assume that highly automated vehicles may only sustain in road traffic, if both human drivers and passengers are willing to accept and use this new technology. Therefore, human factors research should illuminate both human driver and passenger reactions to highly automated vehicles in mixed traffic.

In the context of highly automated driving, previous research mainly focused on the perspective of passengers in transitions from highly automated to manual driving (e.g., Gold et al., 2015; Louw et al., 2015; Petermann-Stock, et al., 2013; Radlmayr et al., 2014; Vogelpohl et al., 2018; Zeeb et al., 2015; see also Vogelpohl et al. 2016 for a literature review), and on passenger comfort during highly automated driving on highways and on rural roads (e.g., Bellem, et al., 2018; Hartwich et al., 2018). While some studies find that the majority of passengers prefer an automated driving style that is similar to their own driving style (e.g., Griesche et al., 2016), other studies show that this is not necessarily the case for passengers to feel comfortable (e.g., Basu et al., 2017). Furthermore, passengers differ in their preferences. For example, older passengers prefer a "young" driving style, which is more dynamic compared to their own driving style (Hartwich et al., 2018).

Having focused on highway scenarios in the past decade, human factors research has now begun to address the question of how highly automated vehicles can handle complex interactions with vulnerable road users such as pedestrians and cyclists in urban areas (Tabone et al., 2021), in both national and international research projects, e.g., @City (2018 – 2022; Fritz et al., 2020), AFiM (2018 – 2021; Mayerhofer et al., 2020; Stange et al., submitted), and SHAPE IT (2019 – 2023; Tabone et al., 2021). Nevertheless, the question of how automated driving behavior in interactions with vulnerable road users affects passengers inside highly automated vehicles, for example, in terms of comfort and perceived risk, is yet to be explored.

Summarizing, the introduction of highly automated vehicles will result in two new types of interactions regarding human interactions with highly automated vehicles in mixed traffic:

The first type of interaction refers to human road user interactions with highly automated vehicles in mixed traffic. This type of interaction will first be relevant on the highway where human drivers will have to interact these highly automated vehicles in the next few years to come. Thus far, numerous studies have focused on the passenger perspective inside highly automated vehicles, neglecting the outside perspective of human drivers in mixed traffic. Thus far, there is only little research available on how human drivers will react to these vehicles (e.g., Fuest et al., 2020; GATEway project, 2017). So, the present dissertation contributes to fill this research gap by illuminating the perspective of human drivers, examining their reactions to highly automated vehicles on the highway both in first contact with these vehicles in selected driving situations and in repeated interactions during longer highway trips.

The second type of interaction comprises the passenger interaction with the automated vehicle as a user of the system. Similar to the first type of interaction, this will first be relevant on the highway. Previous research has extensively investigated passenger’s interaction with the automated system in take-over situations and passenger comfort during automated driving whereas the passenger perspective in interactions with (vulnerable) road users in urban areas is yet to be explored. In the urban driving environment, the configuration of highly automated driving behavior can be expected to have a major impact on passenger comfort. As described, highly automated driving in urban areas is recently gaining attention in the research community and the industry, but is yet understudied (see Tabone et al., 2021). Therefore, this dissertation provides some insights by focusing on the passengers' inside perspective during highly automated driving in interactions with vulnerable road users in urban mixed traffic.

In the following Chapter 2, the theoretical framework of this dissertation is presented. Chapter 2.1 provides an overview over the levels of automation according to the Society of Automotive Engineers (SAE, 2014, 2018) including some examples of driving assistance systems. Chapter 2.2 focuses on the development of automation including estimates of the penetration rates of highly automated vehicles. Based on this theoretical framework, Chapter 3 targets the outside perspective of humans as drivers in mixed traffic. Chapter 3.1 outlines the basic foundations of human driver interactions in non-automated traffic today. Chapter 3.2 then extends this scope to human driver interactions with highly automated vehicles in mixed highway traffic, focusing on the potential compatibility issues that may be accompanied by the introduction of automated systems. Chapter 3.3 focuses on the role of external labelling of highly automated vehicles as a countermeasure to mitigate safety issues in interactions between human drivers and highly automated vehicles. Chapter 3.3 includes the state of research. Chapter 3.4 describes the research gaps that derive from the state of research.

Chapter 4 targets the inside perspective of humans as passengers in mixed traffic. Chapter 4.1 addresses psychological risk theories, providing a definition of risk for this dissertation (Chapter 4.1.1), and transferring the ongoing debate regarding psychological risk on the automated driving context (Chapter 4.1.2). Chapter 4.2 addresses passenger comfort, providing a definition (Chapter 4.2.1), and describing the contributing factors of passenger comfort in highly automated vehicles. Next, previous research on passenger comfort and psychological risk during highly automated driving will be presented (Chapter 4.3). Chapter 4.4 describes the research gaps that derive from the state of research.

In the next step (Chapter 5), the research outline of this dissertation is presented based on the identified research gaps in the previous Chapters 3 and 4. This dissertation then aims to fill the identified research gaps by means of four experimental studies (Chapters 6 to 9). Chapters 6 and 7 include two driving simulator studies from the outside perspective of human drivers in mixed traffic. Study 1 focuses human driver's reactions to highly automated vehicles during first contact in mixed traffic on highways, whereas in Study 2 examines the mid-term effects of highly automated driving on human drivers in mixed traffic, taking into account the increasing penetration rate. Chapters 8 and 9 include a driving simulator study and an online study addressing the perspective of passengers inside highly automated vehicles in mixed traffic in urban areas depending on the configuration of the automated driving behavior. Study 3 targets passenger's perceived risk and comfort in the interaction with a pedestrian in longitudinal traffic. Study 4 addresses passengers' perceived risk in the interaction with pedestrians and cyclists at an urban junction. Based on the results of Study 3 and Study 4, recommendations for the technical design of automated driving behavior are derived for each of the examined driving situations.

The obtained results of the four studies are discussed in the following Chapter 10. This chapter first summarizes the major findings of each study (Chapters 10.1.1 / 10.1.2 / 10.2.1 / 10.2.2). Based on the major findings, this chapter then highlights the lessons learned from this dissertation (Chapters 10.1.3 / 10.2.3), and discusses the (methodological) limitations of the obtained results (Chapters 10.1.4 / 10.2.4). Next, opportunities and recommendations for future research activities regarding the perspective outside of human drivers, and the inside perspective of passengers in mixed traffic are derived (Chapters 10.1.5 / 10.2.5). Finally, conclusions from this dissertation will be presented (Chapter 10.3). Figure 1 shows the outline of this dissertation.

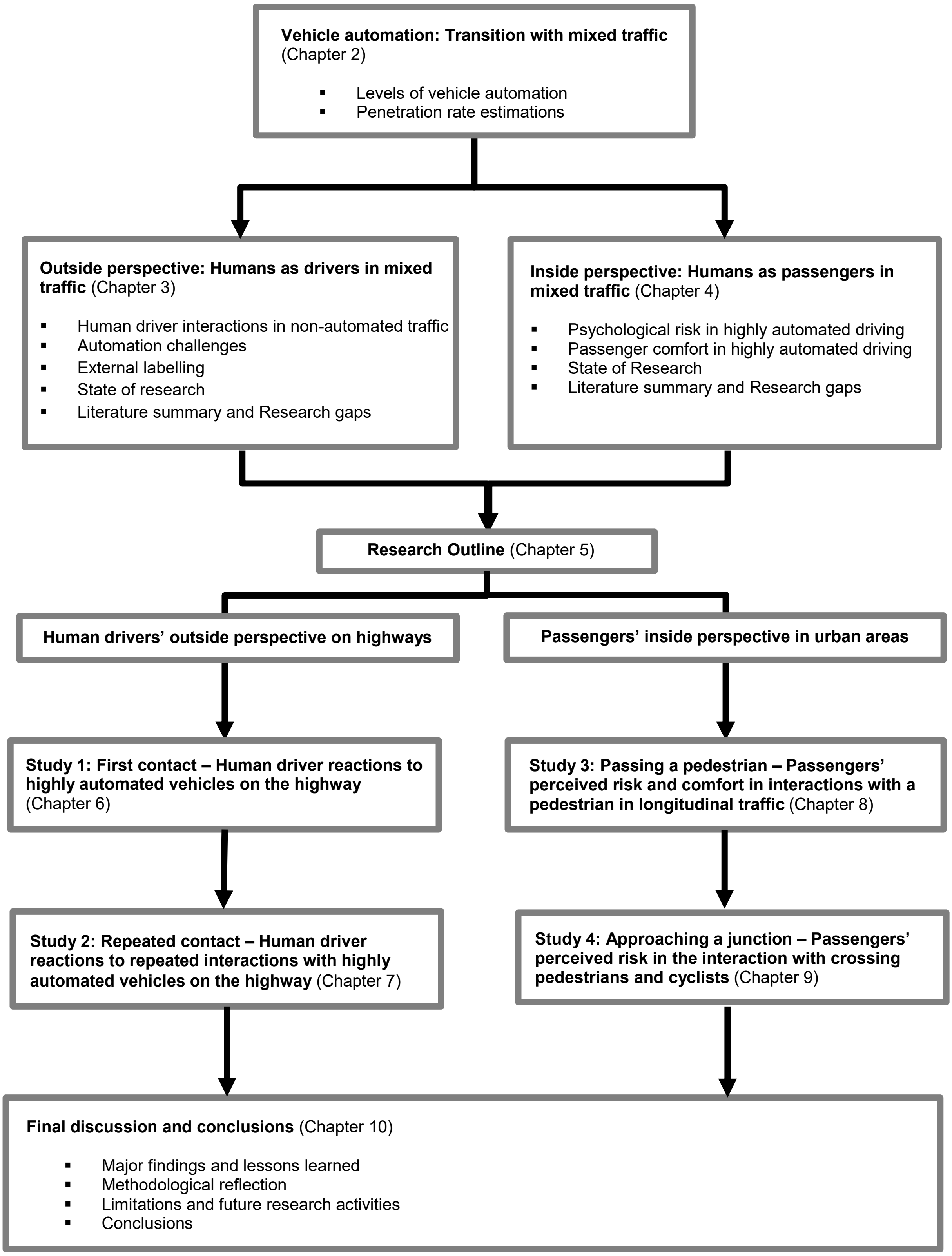


Figure 1 Dissertation Outline.

2 Vehicle automation: The transition phase with mixed traffic

As a starting point for the theoretical framework of this dissertation, the following chapter first describes the levels of automation according to the SAE (2014, 2018) definitions (Chapter 2.1) and then outlines the development of the penetration rate of highly automated vehicles in the near future (Chapter 2.2).

2.1 Levels of vehicle automation

The Society of Automotive Engineers (SAE) distinguishes a total of six levels of automation in the *J3016* standard (SAE, 2014, 2018) which are outlined in the following section.

Level 0 (no automation) corresponds to manual driving without any support by driver assistance systems. At Level 1 (driver assistance), the vehicle takes over either longitudinal or lateral guidance, e.g., (adaptive) cruise control or lane centering. Using cruise control, a freely selectable speed is maintained automatically by the vehicle (e.g., BMW, n.d.; Volkswagen, n.d.). Adaptive cruise control extends cruise control by an automatic distance control, so that the driver is disengaged from the longitudinal guidance, e.g., when driving on the highway, but the driver remains in charge of the lateral guidance (e.g., Audi, n.d.; BMW, n.d.). Using a lane keeping assistance system (with steering), the vehicle takes over lateral guidance and warns the driver (without steering), or corrects its own position within the lane (with steering) if drifted off (e.g., BMW, n.d.-a; Volkswagen, n.d.-a). At Level 2 (partial automation), the vehicle takes over both longitudinal and lateral guidance but the driver must constantly monitor the driving environment and the automated system to intervene at any given time, e.g., the Tesla Autopilot (Tesla, n.d.).

At Level 3 (conditional automation), a paradigm shift takes place as the vehicle temporarily performs the driving task and monitors the driving environment within predefined system limits (SAE, 2014, 2018). Here, the human driver / passenger always serves as the fallback level. Before reaching a system limit, the highly automated system requests the “fallback-ready user” to take over the driving task within a few seconds (SAE, 2018, p. 4). Thus, the human inside the highly automated vehicle has a hybrid function, switching back and forth between the roles of being the active driver and being the passive passenger who may engage in non-driving related tasks. The first Level 3 function will presumably be a traffic jam pilot (Audi, 2017), followed by highway driving beyond congestion (VDA, n.d.; see also Daimler, 2019). From Level 4 onwards, the human driver does not serve as a fallback level anymore. Instead, the highly automated vehicle itself transfers to the risk-minimal state if a system limit is reached. At Level 4 (high automation), the driving task is carried out automatically without any human intervention in limited areas, e.g., in urban areas. Within these areas, it is only necessary for the passenger to take over the driving task if highly automated driving is not available (Wachenfeld et al., 2016). At Level 5 (full automation), the complete drive from start to finish is carried out fully automatically without any human intervention.

The SAE classification system is applied in all studies that are presented in the following chapters of this dissertation (see Chapters 6 – 9).

2.2 Penetration rate estimations

Beyond the introductory phase of highly automated vehicles in the near future, it is difficult to estimate how the penetration rate of these vehicles will develop (Bansal & Kockelman, 2017). Estimations regarding the long-term adoption of highly automated vehicles show a broad variety among experts (Bansal & Kockelman, 2017). For example, Litman (2021) predicted that 50 % of all newly registered vehicles may be automated by 2045, and 50 % of the vehicle fleet may be automated in 2060. Bansal and Kockelman (2017) estimated that between 24.8 % and 87.2 % of private light-duty vehicles will be equipped with Level 4 driving functions by 2045, depending on price declines and customers' willingness to pay. So, the estimates depend strongly on future technological, social and market developments, some of whose effects on the future market are difficult to predict, e.g., shared mobility concepts replacing private car ownership (Bansal & Kockelman, 2017; Litman, 2021; Noy et al., 2018).

Assuming that the first highly automated driving functions will actually be available in 2022 in Germany, the penetration rate in traffic can be estimated using official statistics. According to the Federal Motor Transport Authority, approximately 47.7 million passenger cars were registered in Germany in 2019 (Kraftfahrtbundesamt, 2020a). Approximately 3.6 million new passenger cars are registered each year (Kraftfahrtbundesamt, 2020b). Figure 2 shows the estimated penetration rate over the next 30 years if a certain amount of newly registered passenger cars were highly automated. Under the most optimistic assumption that every newly registered passenger car is equipped with Level 3 functions, all passenger cars would be highly automated by 2035. Even with a still optimistic equipment rate of 50 % of all new vehicles, 100% penetration would not be expected until 2048. An equipment rate of 10 % of all new vehicles would be a slightly more realistic estimation. Based on this estimation, 23 % of vehicles would be equipped with highly automated driving functions in 2050.

However, the number of newly registered passenger cars in the premium and upper middle class segments combined was as low as 4.4 % (approximately 160,000 vehicles) in 2019 in Germany (Kraftfahrtbundesamt, 2020d). So, it is possible that the penetration rate of vehicles equipped with Level 3 functions may increase even slower, reaching an estimated equipment rate of only 9.8 % in 2050.

In summary, the presented penetration rate estimations support previous literature (e.g., Bansal & Kockelman, 2017; Litman, 2021), suggesting that there will be a long transition phase with mixed traffic (Zmud et al., 2019). Therefore, it is reasonable to assume that human drivers will interact with only few highly automated cars over the next few years. So, personal experience with highly automated vehicle behavior may develop very slowly among human drivers. As a consequence, it is reasonable to assume that initial contact with highly automated vehicles will mainly be guided by expectations based on expected benefits and previous experience regarding driver assistance systems.

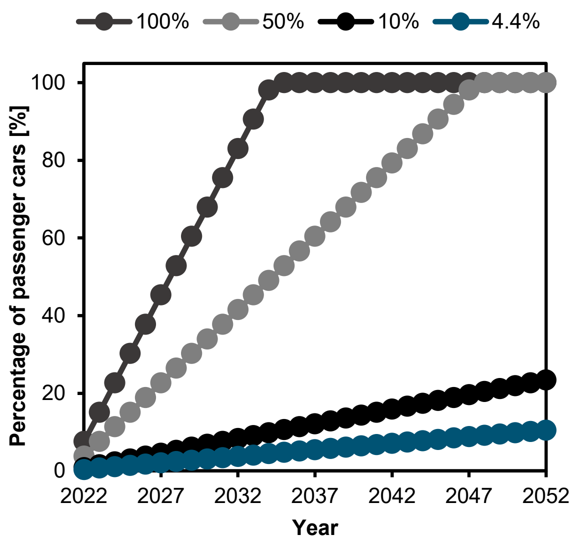


Figure 2 Estimated penetration rate of passenger cars with highly automated driving features until 2052, assuming that 4.4 % 10 %, 50 % or 100 % of all newly registered passenger cars have highly automated driving functions according SAE Level 3.

Although the first Level 3 driving function will be a traffic jam pilot (Audi, 2017), the focus of the first part of present dissertation is on highway driving beyond congestion, with an emphasis on how human drivers will react to these vehicles during first contact in selected driving situations and in repeated interactions during longer highway trips. The following chapter 3 illuminates the interaction between human drivers and highly automated vehicles in more detail. Chapter 3.1 describes the basic principles of human driver interactions in non-automated road traffic. Chapter 3.2 then extends this scope to automation challenges for human drivers in future mixed traffic interactions with highly automated vehicles. Based on the presented challenges of mixed traffic interaction, chapter 3.3 explores external labelling of automated vehicles as a way to counteract the development of false expectations regarding automated driving behavior. Based on this theoretical framework, the state of research on human driver interactions with highly automated vehicles in mixed traffic is then presented in chapter 3.4. Based on the state of research, the main research gaps are pointed out (Chapter 3.5).

3 Humans as drivers in mixed traffic

Currently, human drivers using driving assistance systems up to Level 2 (SAE, 2014, 2018) share the road with other (vulnerable) human road users, and interactions between human road users occur within a commonly shared social framework with (in)formal rules that guide expectations and behavior in road traffic (Hancock, 2020). In the near future, however, human drivers will increasingly interact with highly automated vehicles (SAE Level 3 or higher; SAE, 2014, 2018). As this technology will be introduced in the premium segment first (see Audi, 2017; Holzer, 2020), it is reasonable to assume that human drivers will be in the majority on highways in the next few years, while the penetration rate of highly automated vehicles can be expected to increase rather slowly (see Figure 2). Despite its expected slow development, the introduction of this technology may present human drivers with new challenges as human drivers will have to interact with the automated vehicle itself rather than with the passengers inside the automated vehicle (Schieben et al., 2019), who may perform secondary activities while being driven automatically (Fagnant & Kockelman, 2015). Thus far, human drivers have no experience in interacting with highly automated systems or driving in mixed traffic as these systems are not available on the market yet (see Hetzner, 2020; Holzer, 2020). At the same time, highly automated vehicles may have (noticeably) different driving strategies than human drivers (e.g., Fuest et al., 2020; Nyholm & Smids, 2020; van Loon & Martens, 2015; see also Appendix A), and can be expected to lack an understanding of shared social norms in human road traffic (Hancock, 2020). As a result, human drivers' expectations regarding other drivers' behavior gained from past driving experience with other human drivers may not necessarily apply to highly automated vehicles (Nyholm & Smids, 2020; van Loon & Martens, 2015). Especially during first contact, this may cause wrong anticipations of automated vehicle's future driving behavior as human drivers lack appropriate situation models (Endsley, 1995a), which may result in safety-critical interactions due to the lack of an adequate mutual understanding (Nyholm & Smids, 2020).

Since the human drivers' experience has been limited to interactions with other human road users in non-automated traffic so far, it seems reasonable build on the previous experience of human drivers in non-automated traffic when discussing the potential issues that may arise in mixed traffic. Therefore, the following chapter 3.1 first outlines the basic principles of human driver interactions in non-automated driving, including the situation awareness theory (Endsley, 1995a) and a conceptual framework of interactions in space-sharing conflicts

(Markkula et al., 2020). Chapter 3.2 then describes the new challenges that may arise for human drivers when highly automated vehicles are being introduced on the road.

3.1 Human driver interactions in non-automated traffic

Previous literature pointed out that human drivers aim to arrive safely and efficiently at a destination of travel (e.g., Cnossen, 2000; Fuller, 1984; Summala, 2007). To reach these two driving goals, drivers need to adapt their driving behavior constantly to avoid hazards and handle interactions with other road users successfully (Fuller, 1984; Markkula et al., 2020). As official statistics confirm, the vast majority of interactions runs smoothly as accidents are rare events in road traffic, especially on the highway (Destatis, 2020; Kraftfahrtbundesamt, 2020c). In Germany, the number of accidents with personal injury amounted to approximately 20,000 accidents on highways in 2019, which corresponds to approximately 5 % of all police-recorded accidents with personal injury (Destatis, 2020).

To maintain safe interactions with other road users, human drivers make use of situation awareness (Endsley, 1995a). According to Endsley (1995a, p. 36), “situation awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future” and consists of three levels. Human road users perceive the elements of a current situation (Level 1), comprehend the current situation (Level 2) and project other road users’ future behavior in the driving environment based on their current status (Level 3; Endsley, 1995a). So, human drivers aim to anticipate other road user’s future behavior in order to adapt their own driving behavior to the anticipated development of the driving situation (Endsley, 1995a).

According to Mühl et al. (2020, p. 174), “anticipation relates to a state of ‘cognitive readiness’. The term ‘cognitive readiness’ refers to the factor that drivers are typically prepared for events that are likely to develop in the near future”. So, the concept of anticipation is related to the concept of expectancy (Abelson, 1981; see also Endsley, 1995a; see also Houtenbos, 2008; Preuk, 2017). Alexander and Lunenfeld (1986, p. 8) described expectancy as the “readiness to respond to situations, events, and information in predictable and successful ways”. The authors distinguished between short-term *ad-hoc expectancies* which are developed in concrete situations, and long-term *a-priori expectancies* which are a product of past experience (Alexander & Lunenfeld, 1986). To disentangle the usage of the two concepts in this dissertation, the term *anticipation* is used to describe expectancies in specific driving situations, e.g., the anticipation that a lead vehicle will brake within the next few seconds, whereas the term *expectations* are used to describe long-term, general expectancies, e.g., the expectation that highly automated vehicles will generally improve traffic safety (see Preuk, 2017 for a similar definition).

In order to form anticipations regarding other road users' future actions, human drivers use mental models which are an integral part of the situation awareness theory (Durso & Gronlund, 1999; Endsley, 1995a). Durso and Gronlund (1999) distinguished between mental models as a knowledge structure in the long-term memory on the one hand, and a situation model on the other hand. According to Durso and Gronlund (1999, pp. 297-298), mental models as knowledge structures can be defined as "[…] a representation of the typical causal interconnections involving actions and environmental events that influence the functioning of the system''. On the contrary, Durso and Gronlund (1999) described a situational model as "[…] some slots in the mental model [that] are filled with values gleaned from the environment and other slots in the mental model [that] are filled from the operator's expectations. The situation model can then be 'run' to determine the projected outcome of the operator's planned action" (p. 298). According to the authors, the difference between these two types of mental models is that "the former can exist at a general, abstract level, transcending any particular instantiation; the latter exists in a specific circumstance that arises from the environment and predictions/expectations made by the operator" (Durso & Gronlund, 1999, p. 299).

Although mental models and situation models are being described as separate structures, the two concepts are interconnected as situation models are formed using mental models as top-down memory structures and environmental cues as bottom-up input (Beggiato & Krems, 2013; Durso et al., 2007; Endsley, 1995a). In turn, mental models can contain and trigger a large number of situation models depending on the environmental cues (Durso & Gronlund, 1999). By repeatedly comparing new environmental input with previous experiences stored in a mental model, the mental model can be refined, completed or corrected by means of experience and training (Beggiato & Krems, 2013; Endsley, 1995a; see Holland et al., 1986 for more background on the development of mental models).

In addition to current behavior of other road users as described in the situation awareness theory, human road users use (in)formal traffic rules and the road design to form expectations about other road users' future behavior (Björklund & Åberg, 2005). In the driving environment on highways, it is obvious that the road design has a strong impact on driver expectations of other drivers' future behavior as all vehicles travel into the same direction, with longitudinal movement being limited to acceleration and deceleration, lateral movement being limited to lane changes. Therefore, it is reasonable to assume that in this driving environment vehicle kinematics as implicit communication cues, e.g., acceleration, steering (de Ceunyck et al., 2013; Powelleit et al., 2018), are more essential to interact with other drivers in this driving environment than explicit communication cues, such as e.g., eye-contact, gestures, or mimics (de Ceunyck et al., 2013; Powelleit et al., 2018). An exception from this definition is the use of light signals as explicit communication cues, such as brake lights or indicators which can be expected to be used by drivers on the highway because these signals are legally required (StVO §9, StZVO §53; Federal Ministry of Justice and Consumer Protection, n.d.-a, n.d.-b).

Although there has been a strong focus on human road user interactions across scientific disciplines, there was no commonly accepted terminology surrounding the term *interaction* in this research field (Markkula et al., 2020). Therefore, Markkula et al. (2020) have recently provided an interdisciplinary framework to conceptualize human road user interactions in non-automated and mixed traffic. In this framework, the authors introduced the term *space-sharing conflict*, which is defined as “an observable situation from which it can be reasonably inferred that two or more road users are intending to occupy the same region of space at the same time in the near future” (p. 10). The novelty of this definition is that it also includes conflicts in which a collision between the two road users is possible, in theory, but may never actually occur (Markkula et al., 2020). According to the framework, there are five prototype categories of space-sharing conflicts, including (1) *obstructed path*, (2) *merging paths*, (3) *crossing paths*, (4) *unconstrained head-on paths*, and (5) *constrained head-on paths* space-sharing conflicts.

Transferred to driving on the highway, the first two categories *obstructed path* and *merging paths* appear to be the two most relevant space-sharing conflicts for this dissertation as vehicles usually travel into the same direction on the highway. An obstructed path space-sharing conflict could occur on the highway if, for example, a broken-down vehicle blocks parts of a lane. A merging paths conflict may occur if a lead vehicle changes lanes onto a lane with fast-moving subsequent drivers or if a vehicle accesses the highway merging into flowing traffic on the right lane. In these two examples, the outcome of the space-sharing conflict largely depends on the cooperative behavior of the two road users involved, e.g., the merging vehicle’s acceleration during the lane change and the deceleration of the lag driver on the target lane (see also Kauffmann, 2019). In this driving situation, human drivers use scripts to show appropriate behavior (Houtenbos, 2008). A script is a schema (Schank & Abelson, 1977, as cited in Endsley, 1995a) which “contains a standard sequence of events characterizing typical activities” (Abelson, 1981, p. 715). In the situation awareness theory, scripts are outcomes of mental models that are used to plan and perform actions, i.e. the behavior necessary to achieve an ideal state (goal; Endsley, 1995a).

So, the driver who is aiming to change lanes activates the “lane change script”, knowing that it is necessary to first inform the lag driver in the target lane about lane change decision via the turn indicator and then accelerate to change lane from the right lane to the left lane. In turn, the lag driver has a “merge script” for this lane change situation. The lag driver needs to decide, depending on the distance to the merging vehicle and the driven speed, whether braking and letting the vehicle merge or accelerating to minimize the gap in front, is the better solution to solve the space-sharing conflict. If the lag driver decides to let the preceding vehicle merge, the lag driver can brake to inform the merging vehicle’s driver about this decision or simply maintain the driven speed to keep the gap size constant, i.e. using vehicle kinematics as implicit communication cues (de Ceunyck et al., 2013; Powelleit et al., 2018). Based on this driving behavior, the merging driver can anticipate that the lag driver is willing to let him or her merge in front, which corresponds to the third level of situation awareness (Endsley, 1995a). But what happens if the merging drivers' anticipation of the lag driver's behavior is wrong? For example, if the merging driver anticipates that the lag driver let him or her merge while the lag driver aims to close the gap by accelerating instead. In this case, the merging driver's activated schema and script do not match with the lag driver's behavior, so the merging driver needs to activate a different schema and script, e.g., to abort the planned lane change, which is time-consuming and therefore may increase the driver's reaction time (Houtenbos, 2008).

However, previous research has also demonstrated that human drivers adapt their driving behavior when previously confronted with unexpected driving behavior. For example, Muhrer and Vollrath (2010) examined human driver expectations regarding the behavior of a lead vehicle in a car-following situation in an urban area. In the driving simulator, drivers followed a lead vehicle that showed different types of braking behavior and signaling (signaling vs. no signaling) before turning at an urban intersection. Results showed that drivers were affected by the lead vehicle's driving behavior in the first part of the driving scenario. Drivers who had previously experienced that the lead vehicle braked before turning reacted faster to a sudden braking maneuver of the lead vehicle approaching the intersection. However, this anticipatory driving behavior was a short-lived adaptation as drivers failed to adapt their speed or distance to a lead vehicle in a subsequent car-following situation.

Summing up, human drivers use a multitude of cognitive structures, communicative strategies and interactive behaviors to interact with other human road users successfully. As described, being able to anticipate what the other driver is going to do is essential to successfully avoiding interactions resulting in conflicts or crashes. This anticipation depends on adequate mental models about other human drivers (up to SAE Level 2; SAE, 2014, 2018). But what happens if the other drivers are highly automated vehicles?

Studying human driver interactions with highly automated vehicles provides an opportunity to better understand the importance of mental models and anticipation in the automated driving context. If these structures are indeed essential, then non-model-compliant behavior can be expected to cause issues in mixed traffic interactions. In this respect, the present dissertation examines how important mental models and anticipation are in road interactions, specifically in mixed traffic interactions between human drivers and highly automated vehicles. The following chapter 3.2 extends the perspective of human driver interactions by illuminating the specific challenges for human drivers in mixed traffic when highly automated vehicles are being introduced to the road.

3.2 Automation challenges for human drivers in future mixed traffic

Human road user interactions with (highly) automated vehicles in mixed traffic is a novel research topic for which human factors research is currently beginning to grasp and describe the characteristics and potential issues (e.g., Hancock, 2018, 2020; Noy et al., 2018; Nyholm & Smids, 2020; Stanton et al., 2020; van Loon & Martens, 2015). Due to the fact that highly automated vehicles have not yet been introduced to the market, most of these descriptions of potential conflicts between human road users and automated vehicles in mixed traffic interactions are of speculative nature.

Van Loon and Martens (2015) described two aspects of compatibility issues that may occur in interactions between human drivers and automated vehicles: *backward compatibility* and *forward compatibility*. Backward compatibility is described as the ability of an automated vehicle to anticipate the behavior of a human-driven vehicle based on vehicle kinematics, such as lateral position and acceleration, whereas forward compatibility refers to the ability of a human driver to anticipate the future behavior of an automated vehicle. According to the authors, forward compatibility is reached “when the driving behaviour of automated vehicles is completely indistinguishable from that of human drivers” (p. 3283). Stanton et al. (2020) compared this question of distinguishability between automated and human driving behavior from the external viewpoint to the *Turing test* (Turing, 1950) and the *Chinese Room* experiment (Searle, 1980). The authors argued that automated and human driving behavior may be indistinguishable from an external perspective, yet, at the same time, this is not to imply that automated vehicles act like humans or have a similar way of reasoning (Stanton et al., 2020). Indeed, automated vehicles can be expected to lack understanding of the informal, social rules which human road users use as an implicitly shared basis of knowledge to interact in road traffic (Hancock, 2020).

However, differences in driving strategies between humans and automated systems can be expected regarding, for example, rule-compliance (e.g., Fuest et al., 2020; see Appendix A), so forward compatibility may indeed become an issue. In contrast to highly automated vehicles, human drivers may be less inclined to strive for constant optimization during driving (van Loon & Martens, 2015). As van Loon and Martens (2015) suggested, human drivers may rather perform “satisficing driving” (Hancock & Scallen, 1999, p. 53; see also Summala, 2007). Apart from these expected differences in driving strategies, human drivers may experience negative emotions during driving (e.g., Mesken et al., 2007; Roidl, 2014), which, in turn, is related to risky driving behavior including, for example, small safety margins to preceding vehicles (e.g., Deffenbacher et al., 2002, 2003; Lajunen & Parker, 2001; Mesken et al., 2007; Roidl et al., 2014). Following this reasoning, it human drivers might (to some extent) be able to detect differences between automated and human driving behavior.

On this basis, one may further argue that human drivers lack mental and situation models as well as scripts applicable to highly automated vehicles or that these models gained from experiences with human drivers may not be transferable to driving in mixed traffic (Nyholm & Smids, 2020; van Loon & Martens, 2015). In the context of situation awareness as a conceptual framework for human drivers' first contact with highly automated vehicles as studied in this dissertation, the conceptualization of situation models seems more appropriate than the conceptualization of mental models as long-term memory structures (see Durso & Gronlund, 1999; Endsley, 1995a), since human drivers may have some general expectations regarding interactions in mixed traffic, but no actual experience in interacting with these vehicles yet. Assuming that only a few premium segment vehicles will be equipped with highly automated driving functions (e.g., Audi, 2017; Holzer, 2020; see also Kraftfahrtbundesamt, 2020d), driving automated in specific use-cases such as congested traffic (Audi, 2017; VDA, n.d.), human drivers will first interact with these vehicles in isolated driving situations only (see Appendix A). As a result, human drivers may have an incomplete or inaccurate situation model of automated driving behavior in mixed traffic at first due to the lack of experience or incorrect anticipations, which may result in safety-critical interactions.

In the long run, human drivers may eventually begin to understand the basic principles of automated driving behavior and form mental models being able to anticipate automated driving behavior (more) adequately, and thus contribute to avoid potential safety issues (Noy et al., 2018). Thus far, human factors literature has studied mental models from the perspective of passengers or drivers as users of the technology instead of the external perspective of human drivers (e.g., Beggiato & Krems, 2013; Beggiato, Pereira et al., 2015; Blömacher et al., 2018, 2020; Forster et al., 2019, 2020). Regarding the aspect of forming mental models, it could be speculated that human drivers in non-automated vehicles may not receive as detailed information on the automated systems capabilities and system limits as customers who may receive some information or training when purchasing the vehicle and use this driving function frequently. In this context, previous research has demonstrated that education and training support (first-time) users in the establishment of adequate mental models (e.g., Forster et al., 2019, 2020). So, it is reasonable to assume that human driver reactions to highly automated vehicles in first contact may largely depend on how well automated driving behavior matches with human drivers' individual expectations and previous driving experience in non-automated road traffic.

To bridge this potential gap between human drivers' expectations of the driving behavior of highly automated vehicles and their actual driving behavior, researchers have proposed that the driving behavior of automated vehicles be designed to be human-like (Nyholm & Smids, 2020). However, this idea assumes that human drivers expect automated vehicle to behave human-like in the first place, and it overlooks the broad variety of human driving styles (e.g., Sagberg et al., 2015; Taubman-Ben-Ari et al., 2004). So, it is unclear what exactly *human-like* means in this context. In addition, human drivers may engage in unlawful or risky driving behaviors, so it might be reprehensible to program automated systems displaying such behaviors in a systematic way (see Nyholm & Smids, 2020 for more discussion on this issue). Based on previous literature from passenger comfort research, Ossig et al. (2021) recommended that the development of automated driving styles should not attempt to mimic human driving styles because some passengers may prefer a driving style other than a human-like driving style (see Chapter 4.3 for further results of passenger comfort studies).

Summing up, successful interaction in traffic largely depends on how accurate the anticipation of other drivers' future driving behavior is, which in turn is based on human drivers' scripts and mental models as part of situational awareness. To date, human drivers are experienced in interactions with other human road users, with all of the scripts and mental models being tailored to interactions with other humans. At the same time, it is reasonable to assume that automated vehicles will behave differently than human drivers, at least in a number of situations. These differences between human and automated driving behavior will be particularly relevant for human drivers who do not use highly automated driving functions themselves. Therefore, human drivers will have to rely on their mental models in mixed traffic interactions. Human drivers' first contact with highly automated vehicles appears to be particularly relevant here, since no expectations or mental models can exist there yet, or only minimal, abstract ones. Especially in the first contact, research would have to show that the automated behavior either does not deviate so much from human behavior, or that a safe handling and thus a learning of new mental models is possible.

This learning process could be facilitated if highly automated vehicles would be clearly recognizable from an outside perspective. This could have a positive effect, especially in first contact, as human drivers can then handle the situation more consciously and cautiously. So, a number of studies have examined external labelling of automated vehicles which are presented in the following chapter 3.3.

3.3 External labelling of highly automated vehicles

External labeling of highly automated vehicles has the potential to mitigate human drivers' confusion and frustration and prevent inappropriate interactions based on false expectations as human drivers would be aware of the nature of the vehicle (Brown & Laurier, 2017; Färber, 2016, Stanton et al., 2020). This idea to label highly automated vehicles is quite similar to the marking of driving school vehicles which is legally required in Germany (FahrlG2018DV §5; Federal Ministry of Justice and Consumer Protection, n.d.), as learner drivers may show unexpected driving behavior in a similar way as automated vehicles (Färber, 2016). Beyond compensating for unexpected driving behavior, an external labelling enables automated vehicles to communicate with surrounding human road users in the driving environment (Färber, 2016). In terms of communication content, Schieben et al. (2019, p. 71) identified four types of information which an automated vehicle can convey to human road users via an external human-machine interface (eHMI):

- Information on the current driving mode
- Information on the next driving maneuvers
- Information on the perception of the environment outside the automated vehicle
- Information on cooperation possibilities with the automated vehicle

The first category *information on the current driving mode* includes information on whether a vehicle is currently in automated or manual driving mode. According to Schieben et al. (2019), human drivers could use this information to activate appropriate schemata with stored information on automated vehicles, and to adapt expectations of the automated vehicle's driving behavior adequately. The second category includes information on the vehicle's planned driving maneuvers, supporting human road users in understanding the vehicle's intentions as vehicle kinematics is an essential element in interactions between human road users (Schieben et al., 2019; see also Brown & Laurier, 2017). The third category comprises information on the vehicle's perception of the driving environment, for example, by confirming other road users that they have been detected by the automated vehicle. The fourth category includes possibilities for human road users to cooperate with the automated vehicle, for example, by giving advice to human road users whether it is safe to cross the road in front of the vehicle.

Regarding the highway environment, information on the current driving mode and the next maneuvers seem most relevant, whereas information on the perception of the environment and on cooperation possibilities seem rather important for interactions with (vulnerable) road users in urban areas. Regarding information on the next driving maneuver, it should be noted that highway have separate lanes per direction, so all vehicles travel into the same direction. This infrastructural standardization significantly limits the number of possible driving maneuvers compared to the urban environment. On highways, vehicles can accelerate and decelerate in the longitudinal direction, and perform lane changes in the lateral direction. Therefore, it is questionable whether an additional eHMI about the vehicle's next driving maneuver beyond the legally required light signals would be of any additional informative or even safety-related value for surrounding human drivers (Färber, 2016; see Appendix A). Thus, information on the driving mode would be a better starting point to investigate the effects of an eHMI on interactions with human drivers in the highway driving environment than information on the vehicle's next driving maneuvers (see Stanton et al., 2020).

In line with this reasoning, the majority of the existing eHMI concepts have been designed for application in vulnerable road users interactions in urban areas (Stanton et al., 2020; see also Bengler et al., 2020), especially in interactions with pedestrians (e.g., Clamann et al., 2017; De Clercq et al., 2019; Faas et al., 2020, 2021; Joisten et al., 2020; Hensch et al., 2020; Lagström & Lundgren, 2015; Song et al., 2018; for a review see Rouchitsas & Alm, 2019), and interactions with human drivers in dead-lock situations (Feierle et al., 2020; Rettenmaier et al., 2019, 2020).

Thus far, previous research revealed mixed evidence regarding a positive impact of eHMIs on mixed traffic interactions. Regarding mixed traffic interactions with human drivers in dead-lock situations, Rettenmaier et al. (2019, 2020) found that eHMIs enhanced efficiency in this driving situation by reducing the passing time.

Regarding pedestrian interactions in crossing situations, some studies provided evidence that pedestrians benefit from eHMIs in terms of increased perceived safety (e.g., Böckle et al., 2017; De Clercq et al., 2019; Faas et al., 2020; Habibovic et al., 2018), improved efficiency through faster crossing decisions (e.g., de Clercq et al., 2019; Lagström & Lundgren, 2015), and an increased willingness to cross in front of the automated vehicle (e.g., Lagström & Lundgren, 2015; Song et al., 2018). At the same time, however, other studies reported no significant positive impact of eHMIs on pedestrians' perceived safety, self-reported stress level or crossing behavior (e.g., Clamann et al., 2017; Faas et al., 2021; Joisten et al., 2020; Rodríguez Palmeiro et al., 2018). Based on their findings, Clamann et al. (2017) suggested that gap distances and pedestrians' individual crossing strategies may be more decisive for pedestrians' crossing decision than eHMI information.

Regarding eHMI design to communicate information on the current driving mode or the next maneuver, previous research has mainly focused on visual eHMIs using colored LED light patterns (e.g., Faas & Baumann, 2019; Faas et al., 2020; Hensch et al., 2020; Lagström & Lundgren, 2015), displays mounted on the grill (e.g., Joisten et al., 2019), or light projections on the road (e.g., Powelleit et al., 2020; Rettenmaier et al., 2019; Volkswagen, 2018). Although studies showed that eHMIs had a positive impact on pedestrian crossing behavior, perceived safety, trust (e.g., Lagström & Lundgren, 2015; Faas & Baumann, 2019; Song et al., 2018) and efficiency in interactions with automated vehicles (e.g., de Clercq et al., 2019; Rettenmaier et al., 2019, 2020), light patterns seem to be ambiguous in their meaning (e.g., Hensch et al., 2020; Zhang et al., 2018). In this context, de Clercq et al. (2019) found that a textual eHMI was less ambiguous compared to the other examined eHMI designs (LED light patterns, front brake lights, an anthropomorphist smile). However, eHMIs using textual messages are attached to other understandability issues, for example, for children it would be rather difficult to understand written messages (de Clercq et al., 2019).

Regarding the color of eHMIs, previous research has identified turquoise as a color of choice, arguing that turquoise is a new and unique color in traffic that has no meaning yet, and that turquoise has an overall higher visibility compared to other eligible colors under various lighting conditions (Faas & Baumann, 2019; Werner, 2018; see also SAE, 2019). In a study using structured interviews, Faas and Baumann (2019) compared turquoise and white as eHMI colors showing that pedestrians clearly preferred turquoise over white regarding the aspects of trust, and perceived safety.

Nevertheless, there are no standardized design guidelines for eHMIs regarding the color, display location or reference ("egocentric or allocentric") yet (Bengler et al., 2020; Tabone et al., 2021, p. 3), although standardization could be useful to ensure traffic safety (de Clercq et al., 2019). Given the growing number of eHMI studies, Dey et al. (2020) developed a classification taxonomy to capture and structure the current state of eHMI research as a guide for user interface researchers in developing eHMIs in future work.

As strong argument against the usage of eHMIs, there is a concern that human road users may show abusive or bullying behavior toward automated vehicles (e.g., Connor, 2016; Eliot, 2019; Färber, 2016; Liu et al., 2020; Stanton et al., 2020), especially pedestrians may cross right in front of automated vehicles intentionally as pedestrians know for sure that automated vehicles will definitely brake to avoid a collision (e.g., Färber, 2016; Millard-Ball, 2018). Such behaviors may also affect traffic flow in a negative way (Färber, 2016). Regarding the highway environment relevant to this dissertation, Stange et al. (2020) found in a driving simulator study that, human drivers actively prevented an externally labelled automated vehicle from overtaking a slower truck on the right lane and merging in front of them. In a post-experimental interview, the drivers stated they did not want to be slowed by the automated vehicle or had failed to understand the automated vehicle's intention to change lanes. Although only two drivers showed this kind of intentional bullying behavior, it is reasonable to assume that passengers inside the automated vehicle might not necessarily benefit from other road users identifying the vehicle's automated driving mode immediately. Therefore, the bullying issue will be addressed in the first part of this dissertation (see Study 1 in Chapter 6 and Study 2 in Chapter 7).

Ultimately, further exploration is needed to determine whether abusive behavior will become typical characteristic of human interactions with automated vehicles, or whether this abusive behavior occurs only in some isolated interactions (Liu et al., 2020). Besides, it is yet to be studied whether such negative effects are to be expected on the highway as well or whether this is an issue specific to the urban environment. Färber (2016) argued that the occurrence of such behaviors will largely depend on whether human road users perceive these vehicles as a positive “technological innovation with imperfections” (p. 140), or as a negative “elite status symbol” (p. 140). To protect their vehicles and passengers from being bullied by other manual drivers, Volvo announced that their automated vehicle prototypes will look no different than their non-automated vehicles of the same model (Connor, 2016). Potentially, human factors research will first be able to provide an answer to the potential bullying issue once highly automated vehicles have been introduced to real-world traffic on a larger scale.

Although pervious research demonstrated that eHMIs could be beneficial in urban mixed traffic interactions to some extent, it is hardly possible to draw conclusions from this research for the highway use-case relevant in this dissertation. It remains largely unclear whether and in what respect human drivers would benefit from an external display of, for example, the current driving mode or information about planned driving maneuvers, that exceed the legally required light signals (see Färber, 2016; see Appendix A), and, if so, what type of eHMI design would be feasible or desirable. In a recent study, Stanton et al. (2020) suggested that eHMIs should be visible 360 degrees around the vehicle, so that surrounding human road users would be able to identify the vehicle’s automated driving mode at one glance, and thereby ensure a safe interaction. This eHMI content seems feasible and could be tested in the highway driving environment in the driving simulator.

Thus far, two studies have examined the effect of eHMIs and external recognizability in interactions between automated vehicles and human drivers on the highway (Fuest et al., 2020) or a highway-like multi-lane roads in an urban environment (GATEway project, 2017), which is presented in the following state of research (Chapter 3.4).

3.4 State of research: Human driver interactions with automated vehicles in mixed traffic

To ensure safe interactions with other road users and solve (potential) space-sharing conflicts successfully, previous literature pointed out that it is essential for human drivers to anticipate the driving behavior of other road users correctly, and adjust their own driving behavior in an anticipatory way (Endsley, 1995a; Fuller, 1984; Markkula et al., 2020; Muhrer & Vollrath, 2010). As a consequence, the introduction of highly automated vehicles may present human drivers with challenges as outline in chapter 3.2 which mainly derive from the fact that human drivers lack experience with these vehicles as of yet, and therefore may lack an appropriate situation model or may have inadequate expectations of automated driving behavior (e.g., Nyholm & Smids, 2020; Stanton et al., 2020; van Loon & Martens, 2015; see also Durso & Gronlund, 1999; Endsley, 1995a).

In the context of mixed traffic interactions, previous research has examined in which ways mixed traffic interactions may be challenging for human drivers, investigating human drivers’ ability to distinguish automated and human-driven vehicles in mixed traffic in the first place (Stanton et al., 2020), human drivers' ability to anticipate the driving behavior of highly automated vehicles in comparison to human driving behavior in the same driving situation (Josten et al., 2019), and human driver reactions to (un)expected driving behavior of assisted and automated vehicles (Brown & Laurier, 2017; Preuk, Stemmler & Jipp, 2016; Preuk Stemmler, Schießl et al., 2016; Preuk et al., 2018). Moreover, previous research explored how human drivers react to different types of external recognizability (GATEway project, 2017) and external labelling (Fuest et al., 2020). Finally, Kauffmann (2019) examined what driving behavior human drivers would prefer highly automated vehicles to show on the highway (see also Kauffmann et al., 2018). Although all of the aforementioned studies address mixed traffic interactions from the same human driver perspective, they highlight very different aspects of this research topic. Therefore, the studies and the findings relevant to this dissertation are presented separately.

In an online video survey, Stanton et al. (2020) investigated whether human drivers were able to correctly identify the driving mode of a Tesla Model S based on its driving behavior in a lane change situation on the highway. It should be noted here that the Tesla had no eHMI, so participants were unable to the vehicle's driving mode based on its external appearance. So, participants judged the driving mode solely based on the driving maneuver. To this end, participants were shown 60 short videos, half of which included a Tesla in automated driving mode and the other half included a human-driven Tesla. Results showed that participants were unable to assign the vehicle's driving behavior to the correct driving mode, indicating that the two driving modes were "virtually indistinguishable" (p. 422) from an external perspective of a human driver in the lane change test. Based on this finding, Stanton et al. (2020) argued that this indistinguishability of a vehicle's current driving mode may disturb mixed traffic interactions. For example, in take-over situations where drivers regain control over the driving task they may compromise surrounding human drivers' safety due to unexpected driving behavior after the take-over. In addition, the authors mentioned that human drivers may use nonverbal communication cues tailored to the interaction with human road users to communicate with automated vehicles, which will not be effective in this case. To ensure road safety and communication, the authors suggest the use of an eHMI that displays the vehicle's current driving mode to surrounding human drivers. This allows human drivers to adjust their expectations of the vehicle's driving behavior depending on its driving mode and use appropriate communication cues to interact with automated vehicles, promoting smooth interactions in mixed traffic (Stanton et al., 2020).

Regarding human drivers' ability to anticipate automated driving behavior in comparison to human driving behavior, Josten et al. (2019) investigated human drivers' anticipations of automated and human driving behavior in the same lane change scenario on the highway. In the video-based approach, participants estimated the probability that the target vehicle (highly automated, partially automated, human-driven) driving behind a slow truck on the right lane would in the next few seconds perform (1) no lane change, (2) a narrow lane change in front of the ego vehicle on the left lane, or (3) a lane change behind the ego-vehicle on the left lane. Results showed that participants rated the probability of a narrow lane change higher if the target vehicle was human-driven, and expected automated vehicles to display safe behavior in this situation by either performing no lane change or a lane change behind the ego-vehicle. Josten et al. (2019) attributed these findings to the general public expectation that automated vehicles will increase traffic safety. As a limitation of the study results, Josten et al., (2019) mentioned that participants' anticipations were the product of differences in the basis of evaluation: While the anticipations of automated driving behavior were based only on participants' imagination of highly automated driving behavior, the anticipations of human driving behavior were based on previous experience in non-automated road traffic. Furthermore, the authors pointed out that it is unclear how automated vehicles will behave on a parameter level, for example, at what point an automated vehicle starts to brake. It is therefore unclear, how the expectation of a safety-oriented driving style will match the actual automated driving behavior.

To investigate human driver reactions to unexpected automated driving behavior, Brown and Laurier (2017) used third-party videos from a social media platform analyzing interactions of self-driving vehicles (e.g., Google car, Tesla) and human drivers. Results showed that while most interactions with other drivers were smooth, self-driving vehicles sometimes failed to communicate their intended driving maneuvers to the surrounding manual drivers, thereby confusing human drivers in a number of situations with unexpected driving maneuvers, e.g., by performing unexpected or hesitant lane changes or aborting an intended driving maneuver. Thus, human drivers may have difficulty discerning an automated vehicle's intentions based on its kinematics. In this context, the authors mentioned that Google Waymo has provided all of its self-driving vehicles with external labeling to inform surrounding human drivers of the automated driving capability in order to mitigate human driver confusion by changing human drivers' expectations. Based on their findings, Brown and Laurier (2017) concluded that vehicle kinematics, rather than external labeling of the driving mode, is an essential element of communication in mixed traffic, so automated vehicle can use their kinematics to convey their intentions to its passenger and surrounding human drivers, which, in turn, requires that an automated vehicle has an understanding of how passengers and surrounding drivers will interpret and react to these kinematic cues.

In contrast to the video analysis by Brown and Laurier (2017), Preuk, Stemmler and Jipp (2016) and Preuk, Stemmler, Schießl et al. (2016) used multi-driver simulation to investigate human drivers' reactions to unexpected driving behavior of a confederate driver in an assisted lead vehicle in urban mixed traffic (see also Preuk, 2017). In the study, the confederate was either equipped with a traffic light assistant system including a Green Light Optimal Speed Advisory (GLOSA), and a start-up assistance system or not (baseline condition). The two systems were applied in two use-cases: (1) to avoid unnecessary speed changes when approaching red traffic lights that are about to switch to green (GLOSA), and (2) to stop at larger distance (4 m / 10 m) from a red traffic light and to drive off before signal change (1.3 s / 2.6 s) in order to cross the stop line in the moment of signal change (start-up system). The two participants in the subsequent two vehicles following the assisted vehicle had no previous information on the traffic light assistance system. Results showed that human drivers rated the GLOSA as useful whereas the start-up assistance system received mixed ratings. Negative ratings and small safety margins occurred especially often in the condition with extreme parametrization (10 m / 2.6 s). Moreover, subjective ratings were dependent on participants' position in the platoon. Participants in the first subsequent vehicle rated the assisted vehicle's behavior as more aversively than drivers in the second subsequent vehicle. Based on these findings, the authors concluded that assisted driving behavior may cause safety-critical interactions with subsequent human drivers, the more this behavior deviates from human drivers' expectations (Preuk, Stemmler, Schießl et al., 2016). This conclusion emphasizes the role of (correct) expectations in mixed traffic interactions and is somewhat in line with the findings from Brown and Laurier (2017).

One way to minimize the gap between human drivers' expectations and automated driving behavior, and thus mitigate safety issues and negative emotions, may be to provide information about an automated driving function before interacting with the automated vehicle (Preuk et al., 2018; see also Preuk, 2017). Therefore, Preuk et al. (2018) investigated the role of prior information in a second multi-driver simulator study by providing human drivers with different degrees of information about the assisted vehicle's assistance system (no information, basic information, detailed information) prior to the simulator drive. Human drivers' frustration and behavioral adaptation (speed choice, deceleration) as well as the safety-criticality of interactions (average / minimum time-to collision) were analyzed. Contrary to the authors' hypothesis, prior information failed to reduce non-assisted drivers' frustration, which was largely determined by participants' position in the platoon, with the first subsequent driver being significantly more frustrated than the second one. Moreover, receiving information failed to promote safer interactions with preceding assisted vehicles regardless of the degree of information compared to no information. Instead, some participants who had previously received detailed information maintained shorter time-to-collisions to the assisted vehicle. The authors speculated that these participants may have attempted to understand the assistance system's functionality resulting in shorter distances. At the same time, these drivers showed no changes in speed when approaching the traffic lights, which is beneficial in terms of traffic flow and efficiency (Preuk, 2017).

Focusing on human driver reaction to different types of external recognizability, the GATEway project consortium (2017) used a driving simulator study to investigate interactions between human drivers and highly automated vehicles based on the external recognizability of the automated driving mode in two mixed traffic scenarios in an urban environment: (1) an urban junction and (2) an overtaking scenario on an urban multi-lane ring road. In the driving scenarios, the type of vehicle (automated vs. human-driven) was varied. For the automated vehicles, the external detectability of the automated driving mode was also varied (high: LiDAR sensors on a carrier on the roof; low: sensors on the roof only, without a carrier). In the intersection scenario, the proportion of automated vehicles (high: 80% automated; low: 20% automated; total passing 20 vehicles) in the flowing traffic at the intersection and the gap sizes between vehicles (0.5 s to 6.5 s) were also varied. In the overtaking scenario, the type of subsequent vehicle on the target lane in front of which participants were to merge was varied. In both driving scenarios, subjective ratings regarding aspects of safety, comfort, frustration, and difficulty of the driving maneuver as well as the driving performance of human drivers were analyzed in each trial. Overall, human drivers' subjective ratings were independent of vehicle type, recognizability, or penetration rate of automated vehicles. In the junction scenario, human drivers chose slightly smaller gaps when the penetration rate of automated vehicles was high compared to when the penetration rate of automated vehicles was low. However, the vehicle type (human-driven vs. automated) of the intercepted vehicle had no significant influence on the selected gap sizes. In the overtaking situation, most participants changed lanes only behind the approach vehicle, regardless of vehicle type and the external recognizability of the automated driving mode. So, the external recognizability of automated vehicles did not affect participants' driving maneuvers.

In a driving simulator study, Fuest et al. (2020) examined the effect of labelling automated vehicles on human drivers' subjective evaluation of highly automated driving behavior regarding the aspects of perceived disturbance and appropriateness of the driving behavior, as well as human drivers' behavioral adaptation to these vehicles. In three highway driving scenarios (traffic jam, roadworks, lane change), human drivers followed a highly automated vehicle. In the driving scenarios, highly automated vehicles complied with the traffic rules at all times and drove on the right lane. Results showed that the external labelling neither affected human drivers' subjective ratings nor their driving behavior. Based on these findings, the authors suggested that automated vehicles' driving behavior may already be sufficient as a cue for human drivers to identify automated driving behavior from an external perspective. Regarding the aspect of behavioral adaptation of human drivers, the authors expect behavioral adaptation to occur only after repeated interactions. In the final survey, some participants stated they drove more carefully or maintained larger distances to highly automated vehicles during the simulator drive and would do so in real mixed traffic as well. Some participants indicated they would take the rule-compliance of highly automated vehicles as a role model for their own driving behavior. In contrast this potential role model function, some participants stated that they would display risky driving behavior in interactions with highly automated vehicles as they expect highly automated driving to be “error-free” (p. 10). So, the potential for behavioral adaptation of human drivers is somewhat double-edged.

Finally, Kauffmann (2019; see also Kauffmann et al., 2018) investigated in a series of driving simulator studies what driving behavior would prefer highly automated vehicles to show in congested traffic on the highway. Specifically, the authors have developed a lane change strategy using a variety of parameters. Based on this lane change strategy, human drivers evaluated the driving behavior of a merging lead vehicle equipped with a newly developed lane change and braking algorithm with respect to the aspects of cooperation, safety criticality and ambiguity in congested traffic on the highway. The configuration of the algorithm was developed based on findings from a previous driving simulator study focusing on human lane change behavior and was investigated from the perspective of a following driver driving behind the equipped merging vehicle. Results showed that drivers preferred technical configurations of the algorithm that provided them with more time to adapt their own driving behavior to the lane change intention of the merging vehicle in front than those configurations to which drivers had to react more quickly. Furthermore, an early longitudinal acceleration was perceived as more cooperative compared to a later longitudinal acceleration. The authors transferred the findings from these driving simulator studies to mixed traffic interactions between automated vehicles and human drivers. However, this generalization is only valid to a somewhat limited extent because the link between the technical configuration of the algorithm and vehicle automation was missing in these studies (Kauffmann, 2019, p. 147). Therefore, it is not possible to draw conclusions for the technical configuration of highly automated driving behavior in mixed traffic based on the findings.

Following this overview, the next chapter will summarize the state of the research and use this to derive the research gaps for this dissertation.

3.5 Literature summary and research gaps

Previous research has used different methodological approaches (driving simulation, video studies) to shed light on a variety of mixed traffic interactions in different driving situations, so that many findings currently co-exist without being related to each other. Across studies, the obtained results provide some evidence that interactions with highly automated vehicles in mixed traffic can be challenging for human drivers.

Regarding the question of whether differences between human and automated driving behavior are noticeable from the external perspective of human drivers, Stanton et al. (2020) showed that human drivers and Tesla's autopilot software were indistinguishable from an external perspective when performing a lane change. This indistinguishability may cause communication issues and lead to inappropriate interactions which may be mitigated by means of an external labelling according to Stanton et al. (2020). At the same time, however, previous research has demonstrated that human drivers in mixed traffic were not affected by the external appearance or labelling of automated vehicles (Fuest et al., 2020; GATEway project, 2017). Instead, previous research pointed out that human drivers can recognize automated vehicles based on the driving behavior of the automated vehicle, i.e., the kinematic cues being an essential element in mixed traffic interactions (Brown & Laurier, 2017; Fuest et al., 2020). Therefore, unexpected driving maneuvers of automated vehicles may confuse surrounding human drivers and may eventually result in safety-critical interactions in mixed traffic (Brown & Laurier, 2017). In this context, findings from Preuk, Stemmler, and Jipp (2016) as well as Preuk, Stemmler, Schießl et al. (2016) showed the more automated driving behavior deviates from human drivers' expectations, the more likely safety-critical conflicts may occur. Additional information on the functionality of an automated system does not necessarily mitigate safety-criticality in mixed traffic interactions (Preuk et al., 2018). Still, human drivers' expectation is that highly automated vehicles show more safety-oriented driving behavior compared human drivers in the same situation (Josten et al., 2019).

Following this current state of research, there are two main research gaps being addressed in this dissertation:

To begin with, the findings of previous research indicate that automated vehicle's (noticeably) different driving behavior could lead to safety issues in mixed traffic, especially when the automated driving behavior deviates strongly from human drivers' expectations (Preuk, Stemmler & Jipp, 2016; Preuk, Stemmler, Schießl & Jipp, 2016; see also Preuk, 2017). However, previous research has insufficiently addressed the highway use-case including the relevant driving situations where human drivers will first interact with highly automated vehicle in free driving beyond congestion. For one, the focus of previous research was on use-cases of automated driving in the urban driving environment (see GATEway project, 2017; Preuk, Stemmler & Jipp, 2016; Preuk, Stemmler, Schießl et al., 2016; Preuk et al., 2018). Regarding highway driving environment relevant to this dissertation, previous research has explored congested traffic (see Kauffmann et al., 2018; Kauffmann, 2019), or examined automated vehicles' external appearance in terms of recognizability or labelling whereas behavioral differences between human and automated driving behavior were not included in the experimental manipulation explicitly (see Fuest et al., 2020; GATEway project, 2017). In addition, previous research used video studies in which participants anticipated or observed but not experienced automated driving behavior (e.g., Josten et al., 2019; Stanton et al., 2020). As a consequence, only few conclusions can be drawn about the initial use-case of highly automated driving on the highway. However, as automation behavior will probably be different from the behavior of human drivers in these situations, this might lead to discrepancies with human drivers' expectations and situation models. Thus, it is to be explored for this driving environment how human drivers will react to highly automated vehicles in terms of subjective appraisal and behavioral adaptation.

Furthermore, previous research has focused either on the external appearance of automated vehicles (see Fuest et al., 2020; GATEway project, 2017) or ((un)expected) automated driving behavior (see Josten et al., 2019; Kauffmann et al., 2018; Kauffmann, 2019; Preuk, Stemmler & Jipp, 2016; Preuk, Stemmler, Schießl & Jipp, 2016; Preuk et al., 2018; Stanton et al., 2020). To the author's knowledge, there is no study that combines these two aspects in one study. Thus, if the automation acts differently than human drivers, would an external labelling help human drivers to better anticipate and understand this behavior? Comparing this to (labelled) automation behavior which is similar to human drivers and to deviant automation behavior without labelling allows to better understand the relative contribution of labelling and unexpected behavior.

Moreover, it is yet to be explored how human driver interactions with highly automated vehicles change beyond first contact. It is reasonable to assume that repeated interaction with highly automated vehicles affects human drivers' expectations and behavioral adaptation to these vehicles (Fuest et al., 2020; Josten et al., 2019), as behavioral pattern may become clearer to human drivers beyond first contact. Following the survey results by Fuest et al. (2020), human drivers may adapt their driving behavior to highly automated vehicles which suggests that highly automated vehicles may act as role models for human drivers, ultimately improving rule-compliance. At the same time, it is equally conceivable that human drivers may engage in risky driving behavior in mixed traffic, especially if human drivers assume that they are allowed to make more mistakes themselves because automation operates practically flawless (Fuest et al., 2020), or if human drivers are convinced that automation will protect human drivers in the driving environment by choosing safe driving maneuvers (see Josten et al., 2019). Beyond these findings regarding behavioral adaptation, it can be speculated that repeated interactions, i.e. more experience, helps human drivers to build mental models of typical automated behaviors, thereby improving the ability to anticipate automated driving behavior in various driving situations (see Endsley, 1995a).

This dissertation aims at addressing these research gaps by means of two driving simulator studies (Study 1 and Study 2). To this end, it is necessary to obtain sound knowledge of automated driving behavior, and external appearance as well as the driving situations where human drivers will first interact with highly automated systems on the highway, and to what extent automated and human driving behavior differ in these driving situations. This knowledge can be obtained, for example, through expert interviews (see Chapter 6.2.1; see Appendix A). Based on this preparation, Study 1 examines human driver reactions to highly automated vehicles in first contact, examining four selected driving scenarios where human drivers will presumably first encounter automation. Moreover, the aspect of a direct comparison of automated and human driving behavior is examined as well as the effect of external labelling of automated vehicles. Study 2 extends the scope of Study 1 by investigating human drivers' subjective evaluation and behavioral adaptation in repeated interactions with highly automated vehicles on longer highway sections. In the two studies, human driver reactions are captured both on the subjective level by means of subjective ratings and on the behavioral (objective) level by means of driving data. So, human driver reactions to highly automated vehicles comprise human drivers' situation appraisal, driving behavior, and behavioral adaptation to highly automated vehicles in this dissertation.

The main and specific research questions are further described in the research outline (see Chapter 5).

4 Humans as passengers in mixed traffic

The second part of this dissertation explores the perspective of passengers in urban mixed traffic. In this part, the focus is on the use-case of highly automated passenger cars (SAE Level 4), which are used to drive individual routes in the availability range of automated driving in urban environments (Wachenfeld et al., 2016). This chapter addresses perceived risk (Chapter 4.1), and passenger comfort (Chapter 4.2) during automated driving. Next, the state of research regarding passengers' perceived risk and comfort are presented (Chapter 4.3). Based on the previous literature, the research gaps are derived that this dissertation aims fill (Chapter 4.4).

In the course of increasing vehicle automation (Level 4 or 5; SAE, 2014, 2018), the role of human drivers will change as they become passengers (Rothenbücher et al., 2016), pursuing non-driving related tasks, e.g., reading or talking on the phone (Fagnant & Kockelman, 2015), while the automated driving function takes over the driving task throughout the entire trip (SAE, 2018). Thus far, human drivers' experience with being driven is limited to being a passenger in a human-driven vehicle. So, it can be assumed that passengers are familiar with human driving strategies in interactions with surrounding (vulnerable) human road users in the driving environment. For example, passengers may have previously witnessed how human drivers approach an intersection with poor visibility or how human drivers react to a pedestrian stepping onto the road unexpectedly. Thus, passengers can be expected to have sound knowledge of human drivers' strategies, yet, at the same time, passengers cannot intervene in the driving task themselves. Consequently, passengers' well-being during a trip depends substantially on the driver's driving style and behavior (Ellinghaus & Schlag, 2001). In this respect, one may argue that the role of a passenger in an automated is similar to that of a passenger in a human-driven vehicle, except for the fact that passengers have no experience with being driven automatically yet. In this context, one may argue that passengers find themselves in a similar situation as (manual) human drivers, when being confronted with automated driving behavior for the first time. As has been argued above, there might be difficulties in interactions between human drivers and highly automated vehicles, and the same issue may arise for passengers inside these highly automated vehicles. From their experience of being driven by humans, expectations and mental models have been learned that may not be adequate for automated vehicles (Nyholm & Smids, 2020; van Loon & Martens, 2015). While not having to interact with these vehicles, but being driven by them, this unexpected behavior may lead to discomfort or even anxiety caused by a feeling of risk due to the behavior of the automated vehicle.

Therefore, Bellem et al. (2018) argued that the investigation of passenger comfort in automated vehicles is a new research topic within the field of vehicle automation. In this context, a focus group study showed that expectations of an automated system differed among passengers with little previous knowledge on driver assistance systems, resulting in a potential discrepancy between user expectations and the automated system's functionality as the automated function may operate differently than expected (Josten et al., 2018). Thus, it is reasonable to assume that highly automated driving might cause *discomfort* and a *feeling of risk* in passengers in case the automated vehicle's driving behavior is incompatible with its passengers' expectations (van Loon & Martens, 2015), especially, when passengers are driven by an automated system for the first time. These two psychological constructs are further examined from the passenger perspective in this dissertation.

The following chapters 4.1 and 4.2 provide some theoretical background on the two constructs including definitions (Chapter 4.1.1 / 4.2.1) and contributing factors (Chapter 4.1.2 / 4.2.2). In the context of highly automated driving, previous human factors research has focused on passenger (dis)comfort and examined this construct alongside similar constructs including perceived safety, trust in automation, and driving joy / enjoyment, well-being or subjectively experienced driving performance (e.g., Bellem et al., 2018; Hartwich et al., 2018; Rossner & Bullinger, 2019, 2020a, 2020b; Sauer at al., 2020; Voß et al., 2018). In contrast, passengers' perceived risk during highly automated driving is a yet an understudied research topic (Brell et al., 2019). It can be assumed that all of these psychological constructs are closely linked as they have positive experience as a common theoretical background. In some studies, measurements of these constructs even produce similar results (e.g., Rossner & Bullinger, 2019). However, it is not the aim of this dissertation to illuminate the conceptual differences between these all of these constructs in further detail. Instead, the focus of the present dissertation is on passengers' perceived risk and comfort.

4.1 Psychological risk in highly automated driving

4.1.1 Definition of psychological risk

In non-automated driving, there are three basic types of (psychological) risk: "objective risk, subjective risk estimate and the feeling of risk" (Fuller, 2005, p. 461). The objective risk is the (statistical) probability that an accident will occur (Fuller, 2005). The subjective risk is closely related to the definition of objective risk, describing a driver's individual estimation of the objective probability that a negative outcome such as an accident will occur, i.e. how likely the driver thinks it is that an accident will occur (Fuller, 2005). However, accidents are rare events in traffic as the official statistics prove. In 2019, total mileage on German roads was around 738.8 billion kilometers, of which around 638.3 billion kilometers were driven by passenger cars (85.6 %; Kraftfahrtbundesamt, 2020c). The number of accidents with personal injury involving passenger cars amounted to approximately 300,000 police-recorded accidents (Destatis, 2020). Comparing the number of accidents with personal injury with the annual mileage, this corresponds to one accident with personal injury per 2.46 million kilometers driven. So, the objective probability of having an accident with personal injury is well below 1 %. It is questionable whether drivers are capable of estimating the probability of such rare events (McKenna, 1982). Taking into account that highly automated vehicles are not yet available on the market, estimations of subjective accident risks in mixed traffic would be highly hypothetical. So, the present dissertation focuses on subjective risk as the *feeling of risk* which was previously described as a subjective perception of fear (Fuller, 2005).

The relevance of this feeling of risk for driving has been discussed as an important factor affecting human driving behavior (e.g., Fuller, 1984, 2000, 2005, 2011; Näätänen & Summala, 1974, 1976; Summala, 1988, 2007; Wilde, 1982). When driving manually, human drivers can perform the driving task themselves, and adapt their driving style in such a way that they feel comfortable while driving (see Summala, 2007). According to the Yerkes-Dodson law (1908), driving performance is optimal when the level of arousal is in the mid-range of the inverted U-curve whereas too little arousal results in boredom and fatigue, while too much arousal results in stress and overload (Vollrath & Krems, 2011). But what exactly do human drivers optimize to make them feel comfortable while driving?

4.1.2 Psychological risk theories in the context of highly automated driving

According to the *Theory of Risk Homeostasis* (Wilde, 1982), drivers optimize perceived risk itself while driving. The basic idea is that drivers have an individual target level of risk, i.e., drivers take an individually acceptable risk when driving. To maintain this target risk level, drivers continuously compare their perceived risk in a driving situation with their accepted target risk level. If there is a discrepancy between the desired risk and the experienced risk, drivers adapt their behavior in the respective driving situation, whereby the balance between these two risks depends largely on cognitive and motivational factors. Cognitive factors include, for example, driving experience or distractions while driving. On a motivational level, time pressure or boredom during driving can affect the desired risk. This theory therefore assumes that drivers consciously take a certain amount of acceptable risk, and balance this risk through their driving behavior. Ultimately, drivers always experience a certain amount of perceived risk according to this theory.

In contrast, the *task-capability interface model* (Fuller, 2000, 2005, 2011) suggests that human drivers optimize task difficulty. This optimization includes a continuous comparison of the determinants of task demand and the driver capability to cope with these demands. Ideally, the driver's capabilities are greater than the requirements of the driving situation, so that the driving situation is not experienced as risky. Similar to the *Theory of Risk Homeostasis* (Wilde, 1982), however, drivers also aim to avoid task difficulties that are too low. Instead, drivers continuously aim to achieve an individually optimal task difficulty level while driving which is in accordance with the main assumption of the Yerkes-Dodson law (1908).

Similarly, the *Zero Risk Theory* (Näätänen, & Summala, 1974, 1976; Summala, 1988) assumes that drivers control perceived risk, so that expected risks are avoided in advance or, in case a risky situation has already occurred, to escape this situation as quickly as possible. Risk control is essentially achieved by the adjustment of safety margins which, from the driver's subjective point of view, are large enough to allow sufficient time and spatial distance to a hazard, so that no risk is experienced at all. In contrast to the theories of Wilde (1982) and Fuller (2000, 2005, 2011), drivers do not directly control risk or task difficulty, but safety margins (see also Summala, 2007). However, it remains largely unclear in the Zero Risk Theory, how exactly drivers determine the necessary size of a safety margin in a driving situation (Fuller, 2005).

Transferred to the highly automated driving context, it is reasonable to assume that human drivers expect the highly automated vehicle to optimize either the perceived risk, the difficulty of the task or the safety margins in order to achieve the same or even higher levels of comfort and safety as non-automated driving. Biondi et al. (2019) applied the Yerkes-Dodson law (1908) to the context of automated driving. According to the authors, passengers' performance in secondary tasks is optimal when the level of mental workload is in the mid-range of the inverted U-curve to enable secondary-task engagement whereas too little mental workload may cause drowsiness or mind-wandering, and too much mental workload may cause an overload. Biondi et al. (2018) compared human driver / passenger performance in a peripheral detection task during manual driving and semi-automated driving. Passengers in semi-automated vehicles showed slower reaction times compared to manual drivers as being driven automatically demands less physiological activation. So, one may argue that automated driving is generally less activating than manual driving. Based on these findings, one may hypothesize that highly automated vehicles may have to compensate for the lower activation level by driving in a swift way.

Thus far, it is yet to be explored what levels of risk and comfort passengers prefer during automated driving, and whether passengers are (at all) willing to accept a certain level of perceived risk when being driven automatically (Nolte et al., 2018). In particular, it is yet to be explored how automated driving behavior and driving style affect passengers' perceived risk and comfort in interactions with surrounding human road users, especially vulnerable road users in urban mixed traffic. The current state of human factors research on this topic is presented in chapter 4.3.1.

4.2 Passenger comfort in highly automated driving

From the passenger perspective, comfort is one of the key factors determining whether human drivers will want to use highly automated vehicles and prerequisite for societal acceptance and adoption of this new technology among former drivers (Bellem et al., 2018; Siebert et al., 2013). Therefore, it seems reasonable to examine passenger comfort in highly automated vehicles prior to their market launch.

4.2.1 Definition of passenger comfort

Although a multitude of studies have so far addressed comfort in both non-automated and highly automated vehicles, traffic psychology still lacks a commonly accepted definition of *comfort* (Beggiato et al., 2017; Bellem et al., 2018). According to De Looze et al. (2003, p. 986), there are three key aspects of comfort that previous research agreed on:

> *"(1) comfort is a construct of a subjectively-defined personal nature; (2) comfort is affected by factors of a various nature (physical, physiological, psychological); and (3) comfort is a reaction to the environment."*

Apart from the definition, a yet unsolved conceptual issue is whether comfort and discomfort describe two separate constructs or whether these are the two poles of the same dimension (De Looze et al., 2003). Some authors described comfort and discomfort as two independent, separate constructs (e.g., Branton, 1969; Zhang, et al., 1996). In contrast, Shackel et al. (1969) and Richards (1980, as cited in de Looze et al., 2003) defined comfort and discomfort as two opposite poles of the same continuous dimension.

In this dissertation, it is assumed that discomfort will presumably occur in situations where (some) passengers may perceive the highly automated vehicle’s driving style as risky or dangerous, e.g., if the automated vehicle fails to adapt its speed when approaching a pedestrian crossing. So, discomfort rather refers to a subjective sense of perceived risk as passengers may have different ideas of “risky” or “dangerous” driving behavior. In contrast, comfort refers to a sense of pleasantness which may presumably occur in driving situations where the highly automated vehicle shows anticipatory driving behavior, e.g., by reacting early (enough) to a potential hazard in the driving environment. Again, passengers’ understanding of pleasant driving behavior may vary in the same way as passengers’ discomfort. Following this reasoning, discomfort (= risk experience) and comfort (= pleasantness) are being treated and thus measured separately in the present dissertation.

4.2.2 What factors contribute to passenger comfort?

As comfort is a subjective experience (De Looze et al., 2003), inter-individual differences between passengers can be assumed as to how comfort is achieved. In non-automated driving, it is primarily the driver's driving style that makes a significant contribution to passengers’ well-being whereas in the context of highly automated driving, the automated system is responsible for its passengers’ driving comfort (Bellem et al., 2016; Ellinghaus & Schlag, 2001; Siebert et al., 2013). So, it is reasonable to assume that passengers are exposed to the driving style of the highly automated vehicle’s driving style in quite a similar way as passengers in a human-driven vehicle by the driving style of the human driver.

In the context of non-automated driving, Elander et al. (1993, p. 279), described *driving style* as “the way individuals choose to drive or driving habits that have become established over the period of years”. This definition includes habitual driving patterns such as speed choice, distance keeping, and attentiveness (Elander et al., 1993). Being influenced by a person’s attitudes and beliefs, driving styles are subject to inter-individual differences (Elander et al., 1993; see Sagberg et al., 2015 for a review on driving styles; see also Taubman-Ben-Ari et al., 2004 for a multidimensional investigation of driving style). Similar to differences in human driving styles, it can be assumed that highly automated vehicles may have manufacturer-specific driving styles (see Appendix A).

Furthermore, physical determinants including seat ergonomics, sound, noise, air quality, temperature and vibrations contribute to passenger comfort in non-automated vehicles (Da Silva, 2002; Elbanhawi et al., 2015; Fard et al., 2014). As automation progresses, physical determinants of comfort are supplemented by automation-specific aspects that contribute to passenger comfort, namely *naturality* of automated driving behavior, and *apparent safety* (Elbanhawi et al., 2015). *Naturality* describes the execution of human-like driving trajectories to mitigate passengers' impression of being driven by a robot (Elbanhawi et al., 2015). Here, the underlying assumption is that passengers may feel more comfortable if the automated driving style is somewhat familiar to them. At the same time, passengers may even expect an automated vehicle to show human-like driving behavior, which, in turn, may affect acceptance (van Loon & Martens, 2015). The second aspect, *apparent safety* can be described as a feeling of safe operation, which could be established by maintaining large distances to moving and static obstacles in traffic, early reactions to changes in the driving environment, and a smooth execution of driving maneuvers (Elbanhawi et al., 2015).

In the *Comfort Zone Model*, Summala (2007) identified four aspects determining driver comfort in non-automated vehicles, including (1) *vehicle-road system*, (2) *good progress of trip*, (3) *rule-following*, and (4) *safety margins*. Most relevant in the context of passenger comfort in highly automated driving is the aspect of safety margins (Siebert et al., 2013). According to Summala (2007, p. 199) "the 'comfort zone' implies sufficient time and space margins around the driver, that is to road edges, obstacles, other vehicles and, finally, to a crash. Safety margins are understood as being the major tool for survival and the major control variable". The larger the safety margin to a (non-) moving obstacle, the more time a driver has to react in a safe manner, avoiding a collision (Siebert et al., 2013). In non-automated driving, the size of safety margins is highly individual whereas in highly automated vehicles safety margins are subject to pre-defined configurations of the automated system regardless of driver preferences (Siebert et al., 2013).

However, it can be assumed that highly automated vehicles of the first generation will maintain large safety margins to surrounding vehicles, probably larger ones than human drivers would keep (see Appendix A). It is yet unclear to which extent passengers will be able adjust the pre-defined configurations themselves. To meet passenger expectations and enhance comfort, researchers recommend that passengers should be offered some options for personal customization of automated driving styles (e.g., Beggiato et al., 2017; Dettmann et al., 2021; Griesche et al., 2016; Ossig et al., 2021; Scherer et al., 2016).

In summary, a multitude of factors contribute to passenger comfort as described in the previous section. Although some theories and findings from research on driver comfort in non-automated vehicles may be transferred to the field of passenger comfort in highly automated vehicle, this is a new research field (Bellem et al., 2018).

4.3 State of Research: Passengers' perceived risk and comfort

Previous human factors research has strongly focused on passenger comfort, whereas perceived risk in the context of highly automated driving is yet to be explored (Brell et al., 2019).

The focus was on passengers' driving style preferences, and similarities to human driving style (e.g., Basu et al., 2017; Beggiato et al., 2017; Cramer et al., 2020; Griesche et al., 2016; Hartwich et al., 2018; Scherer et al., 2016), as well as the influence of a passenger's personality and age on comfort (Beggiato et al., 2017; Bellem et al., 2018; Hartwich et al., 2018). Moreover, some studies investigated trajectory adaptation as a reaction to other drivers in the driving environment, for example, in oncoming traffic on rural roads (Rossner & Bullinger, 2019, 2020b). In the urban driving context, a driving simulator study examined the effect of time pressure on passengers' emotional state during automated driving (Techer et al., 2019).

Regarding passengers' preference of highly automated driving styles, and the similarity to their own driving style, evidence is mixed. Griesche et al. (2016) found that most passengers preferred a driving style similar to their own whereas a minority of passengers preferred an unfamiliar driving style. Therefore, the authors suggested that passengers should be able to choose from a set of predefined driving styles as a complete customization of automated driving styles to individual passengers may challenge safety verification of automated driving functions too much (Griesche et al., 2016). In contrast, Scherer et al. (2016) found no evidence that passenger comfort was increased if the automated driving style was similar to their own driving style. In addition to their own recorded drive, participants experienced a slower and a faster automated driving style in the study, showing no significant differences in the global evaluation of comfort. Following from these results, Scherer et al. (2016) recommended a universal automated driving style which, at the same time, may include some predefined customization options. In line with this finding, Cramer et al. (2020) examined passenger comfort using three driving styles (right lane only, cautious, dynamic) in a real-world driving study on the highway. Results showed no significant differences for passengers' comfort and discomfort ratings of the three driving styles. Instead, passengers' self-reported comfort was high for all three driving styles examined in the study. In a driving simulator study by Basu et al. (2017), passengers experienced four automated driving styles, (1) a defensive, (2) an aggressive, (3) their own driving style (by watching a replay of their previous manual drive), and (4) a distractor driving style (by watching a replay of a different participants' manual drive). Results revealed that passengers preferred a significantly more defensive driving style compared to their own driving style, although over 80 % of the passengers thought they had chosen their own driving style as their preferred driving style.

Furthermore, previous research examined inter-individual differences regarding the preference of a driving style due to driver characteristics, such as age (Hartwich et al., 2018), and personality (Beggiato et al., 2017) with mixed evidence. Younger drivers (25 – 35 years) preferred familiar automated driving styles whereas older drivers (65 – 84 years) preferred unfamiliar, faster, and thus “younger” driving styles (Hartwich et al., 2018). Passengers with higher levels of extraversion, higher annual mileage and lower need for control reported higher levels of comfort whereas passengers with higher levels of neuroticism and introversion as well as a higher need for control reported lower levels of comfort and driving enjoyment (Beggiato et al., 2017). In contrast, Bellem et al. (2018) found no effect of passengers’ personality traits on their automated driving style preferences. However, drivers’ preference was partly dependent on their own driving style, as measured by the *Multidimensional Driving Style Inventory* (MSDI; Taubman-Ben-Ari et al., 2004). Passengers who scored lower on risky driving style preferred earlier acceleration onsets compared to human drivers with higher scores on this dimension.

Despite the mixed evidence obtained regarding passengers’ preferred driving style, previous research largely agrees that passengers reject high longitudinal or lateral acceleration rates or jerks as well as short safety margins to other vehicles (e.g., Bellem et al., 2018; Griesche et al., 2016; Scherer et al., 2016). Instead, passengers prefer a smooth, steady execution of driving maneuvers and an early reaction to an obstacle or a (potentially) hazardous situation (e.g., Bellem et al., 2018; Elbanhawi et al., 2015; Griesche et al., 2016; Scherer et al., 2016).

From a technology-driven perspective, it can be assumed that automated vehicles drive in the center of the lane with similar deviations as in human driving (see Appendix A). However, Voß et al. (2018) pointed out that technically ideal trajectories may not necessarily meet with human drivers’ preferences regarding lateral vehicle control, as preferences depend on the cues from the driving environment, such as oncoming traffic. So, there is a need for adaptation of trajectories in automated driving as a reaction to external cues in the driving environment (Rossner & Bullinger, 2019, 2020b; Voß et al., 2018).

Thus, it is reasonable to assume that such behavioral adaptation may also be relevant in dense urban mixed traffic where highly automated vehicles will interact with pedestrians and cyclists, for example in longitudinal traffic with oncoming traffic and interactions with vulnerable road users. In the urban driving context, previous research has demonstrated that pedestrians use vehicle kinematics as a visual cue to interact with (automated) vehicles (e.g., Fuest et al., 2018, 2019; Lee et al., 2020).

Moreover, Techer et al. (2019) examined the effect of time pressure during automated driving on passengers’ emotions and passenger-induced take-overs in a driving simulator study. The study included urban driving situations such as congestion and waiting at a pedestrian crossing. Participants were assigned in two groups: time pressure or control group. Results showed that under time pressure, there were more passenger-induced take-overs compared to the control group without time pressure. At the same time, however, time pressure was also named the most frequent reason for driver-induced take-overs in the control group. Other reasons for passenger-induced take-overs were saving time, interactions with other road users, incomprehension of automated driving behavior, driving behavior being too cautious, and lack of trust in the automated vehicle. Comparing passengers' emotions in the two groups, time showed no significant effect on any of the measured dimensions including anger. Instead, all participants were significantly angrier after the automated drive regardless of time pressure. The authors attributed this result to the cautious automated driving style and named driver-induced take-over as a way to cope with frustration over automated driving style or handling of a specific driving situation. In addition, these results underline the importance of automated driving style in urban areas for the well-being of passengers, as Level 4 vehicles are to be operated without human intervention (SAE, 2018; Techer et al., 2019). Therefore, the requirement for automated driving behavior in urban areas should be that they drive so well and master the interactions with (vulnerable) road users in the driving environment so smoothly that passengers have a positive driving experience, and do not feel inclined to take over the driving task (Techer al., 2019).

4.4 Literature summary and research gaps

Summing up, previous studies have demonstrated that automated driving behavior determines passenger comfort during a highly automated trip. Despite the heterogeneous evidence on passengers' automated driving style preferences, there is a consensus in the human factors literature on how passenger comfort can be achieved during automated driving. Previous studies have shown that an early response to changes in the driving environment and physical factors such as steady operation, low longitudinal and lateral acceleration and jerk have a positive impact on passenger comfort (e.g., Bellem et al., 2018; Griesche et al., 2016; Rossner & Bullinger, 2020b; Scherer et al., 2016; see Ossig et al., 2021 for an overview). In addition, previous research suggests that adjusting the trajectory to the conditions of the driving environment enhances passengers' perceived safety and subjectively experienced driving performance (Rossner & Bullinger, 2019; Voß et al., 2018).

Following from this current state of research, there are two main research gaps regarding passengers' perceived risk and comfort in mixed traffic interactions that this dissertation aims to fill:

First, the general focus of previous research has been almost exclusively on passenger comfort, while the aspect of perceived risk in highly automated driving is yet understudied (Brell et al., 2019). Secondly, passenger comfort in highly automated vehicles has so far been investigated on highways (e.g., Bellem et al., 2018; Cramer et al., 2020; Griesche et al., 2016; Rossner & Bullinger, 2020a), on rural roads (e.g., Rossner & Bullinger, 2019, 2020b; Voß et al., 2018), or in a combination of these two road types (e.g., Hartwich et al., 2018). Thus, previous research has not yet sufficiently investigated how passengers want to be driven in highly automated vehicles in urban areas and how passenger comfort is achieved in this use-case. In the context of urban driving, Techer et al. (2019) have provided initial insights into the emotions of passengers during highly automated driving. However, the focus of the driving simulator was more on an entire automated trip than on specific mixed traffic interactions with pedestrians and cyclists. For such interactions it is yet to be explored how automated vehicles should operate from a passenger perspective.

Hence, it is proposed to first examine frequently occurring *space-sharing conflicts* (Markkula et al., 2020) where highly automated vehicles interact in direct contact with vulnerable road users, e.g. at junctions or in longitudinal traffic when crossing the road. Following the framework of human road user interactions (Markkula et al., 2020; see Chapter 3.1), two types of space-sharing conflicts are examined in this dissertation, (1) a *crossing paths* conflict, where a highly automated vehicle approaches a junction with crossing vulnerable road users, and (2) an *obstructed path* conflict, where a highly automated vehicle passes a parking stand with pedestrians being obstructed by the parking vehicles. For these two driving situations, it is investigated how specific configurations of driving behavior affect passenger comfort and the perceived risk. As previous research has shown, an automated vehicle may also need to adapt its driving behavior as a reaction to the driving environment (Rossner & Bullinger, 2019; Voß et al., 2018). Therefore, in addition to the driving style as a whole, the effect of certain driving behavior adjustments including safety margins to surrounding road users in the driving environment as well as deceleration speed and lane guidance on passenger comfort and perceived risk should be examined in more detail.

This dissertation aims to fill these research gaps by means of two psychological studies, a driving simulator study (Study 3) and an online study (Study 4) addressing how highly automated vehicles should drive so that passengers feel comfortable and what level of perceived risk passengers accept during automated driving. These two studies are further outlined in the following chapter 5.

5 Research Outline

Highly automated vehicles will first be introduced on highways (e.g., Audi, 2017; Daimler, 2019; VDA, n.d.; see Appendix A). For this introductory use-case, previous research has extensively examined the passenger's perspective addressing both the driving performance in take-over situations (e.g., Gold et al., 2015; Louw et al., 2015; Petermann-Stock, et al., 2013; Radlmayr et al., 2014; Vogelpohl et al., 2018; Zeeb et al., 2015; see Vogelpohl et al., 2016 for a literature review), and passenger comfort during automated driving (e.g., Bellem, et al., 2018; Cramer et al., 2020; Griesche et al., 2016; Hartwich et al., 2018). However, it is yet understudied how human drivers in non-automated vehicles will react to highly automated vehicles in mixed traffic interactions on the highway. Thus, two studies were conducted to explore short-term (first contact) and mid-term effects (repeated interactions) of highly automated vehicles in mixed traffic.

The next step of development will transfer this new technology to urban environments which has recently come into focus in human factors research (Tabone et al., 2021). Due to the complexity of the urban driving environment, the development of driving strategies and the corresponding trajectory planning are challenging (e.g., Hubmann, 2016; Nolte et al., 2018). At the same time, previous research has shown that the technical configuration and adaptation of automated driving behavior to the driving environment is a key factor contributing to create passenger comfort (see Rossner & Bullinger, 2019; Voß et al., 2018). So, it is reasonable to assume that the configuration of automated driving style will be especially important in complex urban situations where passengers will witness how highly automated vehicles will interact human pedestrians and cyclists from a passive position, but, ideally, not intervene in this interaction (see Techer et al., 2019). Thus, the second part of the dissertation includes two studies focusing on passenger comfort and perceived risk during automated driving in to order to promote a human-centered development of highly automated driving functions in urban mixed traffic interactions.

Thus, this dissertation comprises a total of four psychological studies, three experimental driving simulator studies (Study 1 – 3) and one online video study (Study 4). Study 1 (Chapter 6) and Study 2 (Chapter 7) aimed to examine human driver reactions to highly automated in mixed traffic on the highway whereas Study 3 (Chapter 8) and Study 4 (Chapter 9) targeted the perspective of passengers inside highly automated vehicles in typical interactions with pedestrians and cyclists in urban mixed traffic. Figure 3 summarizes the research outline of this dissertation. In the following chapter, the main and study-specific research questions as well as the experimental outline of each study are described.

5.1 Study 1: First contact – Human driver reactions to highly automated vehicles on the highway

Thus far, human drivers have no experience with highly automated systems or driving in mixed traffic on the highway yet as these systems are not available on the market yet (see Hetzner, 2020; Holzer, 2020). In addition, human drivers' expectations regarding other drivers' behavior gained from past driving experience is limited to other human road users, and may not apply to highly automated vehicles (Nyholm & Smids, 2020; van Loon & Martens, 2015), as these vehicles may have (noticeably) different driving strategies than human drivers (Fuest et al., 2020; van Loon & Martens, 2015; see also Appendix A). So, Study 1 focused on human driver reactions to these vehicles in first contact, and addressed the main research question:

1. How do human drivers react to highly automated vehicles at first contact in mixed traffic on the highway?

To answer this main research question, human drivers interacted with highly automated and human-driven target vehicles in four selected driving situations on the highway (S01 – S04) covering two types of interactions between human drivers and automated vehicles. In S01 and S02, target vehicles reacted to participants' driving behavior whereas in S03 and S04, participants had to react to the driving behavior of target vehicles (see Table 1). In these driving situations, the specific research questions (see Figure 3) targeted the external distinguishability of automated and human-driven vehicles from a human driver's outside perspective (RQ 1.1), human drivers' perceived safety and comfort (RQ 1.2) as well as the safety-criticality of mixed traffic interactions (RQ 1.3). Furthermore, the effect of an external labelling of the automated driving mode (no labelling, correct labelling, incorrect labelling) on human drivers' subjective ratings and driving behavior was investigated (RQ 1.4).

5.2 Study 2: Repeated contact – Human driver reactions to repeated interactions with highly automated vehicles on the highway

Study 2 extended the scope of Study 1 by exploring human driver reactions to highly automated vehicles in repeated interactions during longer highway trips. Based on previous research (Fuest et al., 2020; Josten et al., 2019), it was hypothesized that repeated interactions with highly automated vehicles might affect human drivers' expectations of highly automated driving behavior and their own driving behavior. On the one hand, it is conceivable human drivers may become acquainted to highly automated driving behavior after some exposure time and start to adapt this driving behavior, thereby enhancing compliance with the traffic rules. On the other hand, it is equally conceivable that human drivers may perceive highly automated vehicles as slow-moving obstacles resulting in risky driving behavior and safety-critical interactions. As these expected positive and negative effects on human drivers may depend on the penetration rate of highly automated systems, this was also addressed by systematically varying the penetration rate (see Figure 2), Study 2 pursued an explorative approach, addressing the main research question:

2. How do human drivers react to highly automated vehicles in repeated interactions during longer trips in mixed traffic on the highway?

To this end, four highway sections (35 km each) including the four driving scenarios (S01 – S04) from Study 1 were implemented in the driving simulator. On these highway sections, the penetration rate of highly automated vehicles was systematically varied in four steps from 0 % to 75 %. Thus, the increase in the penetration rate of highly automated vehicles after their introduction on public roads could be simulated. In addition, the external labelling of the highly automated driving mode (no labelling / correct labelling of the automated driving mode) was varied to investigate whether such an external labelling affects human drivers' behavior in mixed traffic.

Similar to Study 1, Study 2 focused on the external distinguishability of highly automated and human-driven vehicles (RQ 2.1) as well as human drivers' perceived safety (RQ 2.2), comfort (RQ 2.2) and emotions (RQ 2.3) during the simulator drive. Furthermore, Study 2 explored highly automated vehicles' potential role model function for human drivers in terms of rule-compliance (RQ 2.4) as well as human drivers' behavioral adaptation to an increasing penetration rate of highly automated vehicles in mixed traffic (RQ 2.5). In addition, the potential benefits and issues of an external labelling of highly automated vehicles were further explored (RQ 2.6).

As described, previous human factors research has extensively investigated the perspective of passengers. Especially the handling of passengers with the system limits of automation was addressed in detail. So, the passengers' perspective on the highway was not further investigated in this dissertation. Instead, this dissertation aimed to explore the passengers' perspective during automated driving in urban mixed traffic interactions as this use-case of highly automated driving is yet understudied. For the urban use-case where highly automated system will be introduced much later (see VDA, n.d.; Tabone et al., 2021; see Appendix A), it is reasonable to assume that the technical configuration of automated driving behavior may be less advanced compared to the highway use-case. So, the perspective of passengers in the vehicle can be taken into account in the (technical) development of these systems.

Therefore, Study 3 (Chapter 8) and Study 4 (Chapter 9) examined the inside perspective of passengers inside highly automated vehicles in urban areas (Level 4). The focus was on two types of space-sharing conflicts (Markkula et al., 2020) in longitudinal traffic and at an urban junction.

5.3 Study 3: Passing a pedestrian – Passengers' perceived risk and comfort in interactions with a pedestrian in longitudinal traffic

In urban mixed traffic, passengers observe from passive position inside the highly automated vehicle how the system interacts with other human road users in the driving environment, including pedestrians and cyclists. As described in the previous chapters of this dissertation, human drivers have no experience with being driven in highly automated vehicles as these automated systems are not available yet. In addition, urban areas include complex interactions with vulnerable road users where automated systems need to react to sudden changes in the driving environment in a flexible way e.g., due to visual obstruction or unexpected pedestrian behavior (Nolte et al., 2018; Völz, 2020). As a result, it is yet unclear how passengers in their passive position will react to the automated system handling interactions with pedestrians and cyclists in urban mixed traffic. Study 3 focused on pedestrian interactions in longitudinal mixed traffic, addressing the main research question:

3. How do passengers want to be driven in a highly automated vehicle when passing a visually obstructed pedestrian on a parking stand?

To answer this main research question, an urban main road with a parking stand on the right-hand side was implemented in the driving simulator. In the first part of the study, passengers experienced a number of pre-defined configurations of highly automated driving behavior which were developed in cooperation with function developers. The focus was on passengers' perceived risk and comfort depending on variations in the automated driving parameters (speed, lateral offset, deceleration) and the presence of a pedestrian on the parking stand as well as oncoming traffic (RQ 3.1). In this first part of Study 3, it was however not possible to examine all possible driving parameters that may affect passengers' perceived risk and comfort. Therefore, passengers were asked to drive themselves as they would ideally like to be driven in a highly automated vehicle in the second part of the study (RQ 3.2). This was done to validate the pre-defined configurations of highly automated driving behavior and to examine whether there are further driving parameters in the highly automated driving function that are relevant for passengers' perceived risk and comfort.

5.4 Study 4: Approaching a junction – Passengers' perceived risk in the interaction with crossing pedestrians and cyclists

Following on from Study 3, Study 4 further explored a second, "standard" driving situation in urban mixed traffic, i.e. approaching a junction with crossing pedestrians and cyclists. Study 4 examined the following main research question:

4. How do passengers want to be driven in a highly automated vehicle when approaching an urban junction with crossing pedestrians and cyclists?

To this end, a "standard" junction where passengers interacted with pedestrians and cyclists was implemented in the driving simulator. In this driving scenario, the speed of the highly automated vehicle (30 km/h, 50 km/h), the type of vulnerable road user (pedestrian, cyclist), and the direction from which the vulnerable road user crossed the junction (left, right) were varied. Study 4 explored passengers' ideal (RQ 4.1) and the last accepted (RQ 4.2) braking onset time when approaching the junction. In contrast to Study 3, passengers could manually control the highly automated vehicle's driving behavior by triggering the braking onset while approaching the junction themselves instead of experiencing pre-defined configurations. In a second step, participants could either confirm or correct their manually adjusted braking onset once. After the final confirmation, participants rated perceived risk for the previous interaction to address the question of how much risk passengers are willing to accept in the interaction with pedestrians and cyclists (RQ 4.3).

The following four chapters (Chapter 6 to 9) include the described four studies conducted in this dissertation. The results of the studies will be discussed in the final Chapter 10.

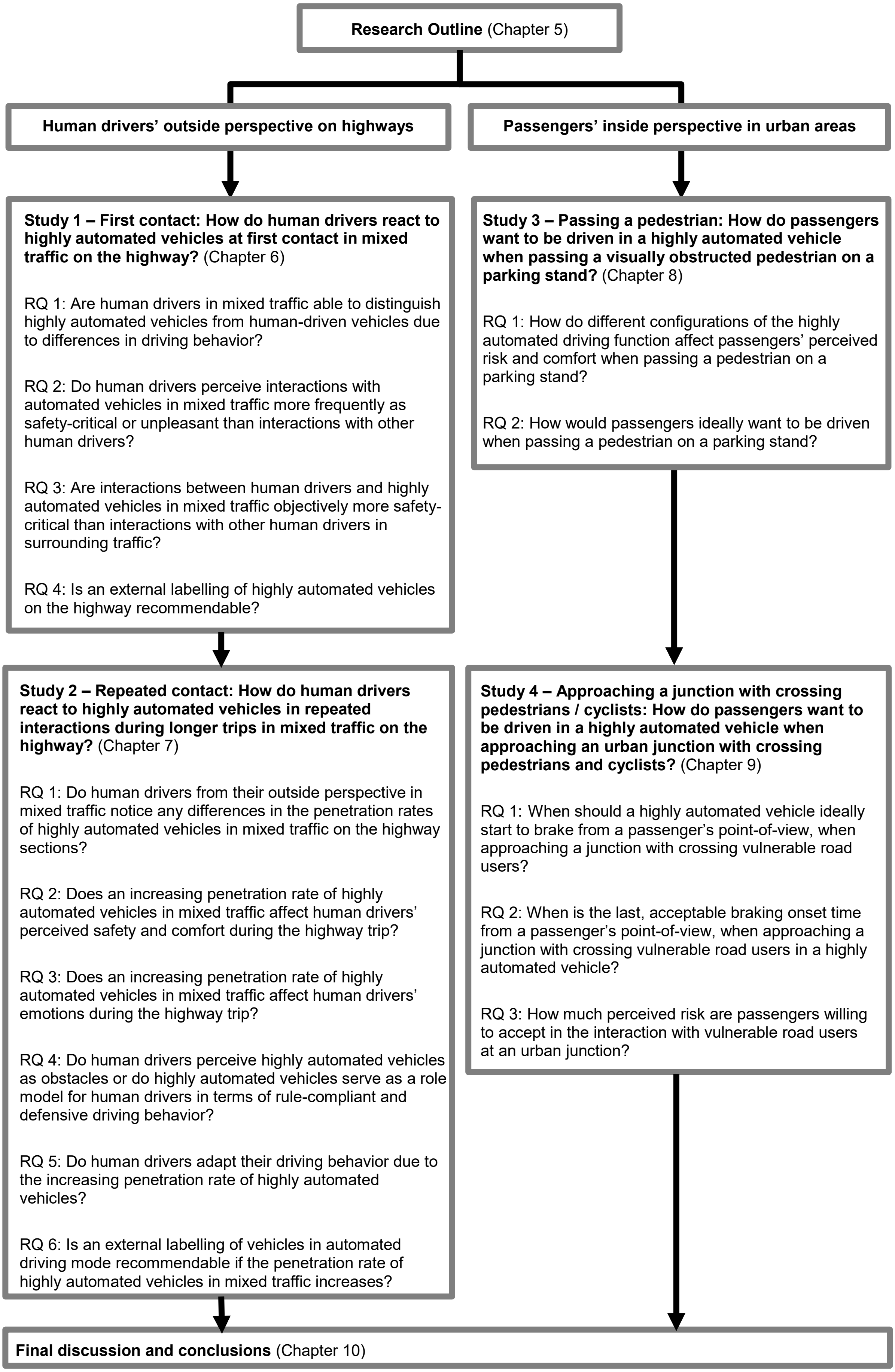


Figure 3 Research outline.

6 Study 1 – First contact with highly automated vehicles on the highway

6.1 Objective and research questions

In the near future, highly automated vehicles (Level 3; SAE, 2014, 2018) will be introduced on the highway (Audi, 2017; Daimler, 2019; see Appendix A), resulting in long transition phase with mixed traffic where human drivers and will share the road with highly automated vehicles (see Chapter 2). It can be assumed that highly automated vehicles will behave differently than human drivers in a number of driving situations (Fuest et al., 2020; van Loon & Martens, 2015), showing more defensive and rule-compliant driving behavior than human drivers (see Appendix A). So, previously gained driving experience from interactions with other human drivers and the expectations of other drivers' behavior formed on this basis may not be transferable to interactions with highly automated vehicles (Nyholm & Smids, 2020; van Loon & Martens, 2015). In addition, highly automated vehicles can have manufacturer-specific driving styles similar to differences in human driving style (see Appendix A). However, further exploration is need to examine whether and in which driving situations the configuration of automated driving will be within or outside of the range of possible human driving behavior (see Appendix A; see also Stanton et al., 2020).

Based on these considerations, Study 1 addressed the question of how human drivers will initially react to highly automated vehicles that may behave differently than human drivers would in the same situation (see Chapter 5.1). The aim of the present study was therefore to examine human drivers' reaction to this different behavior or to potential behavioral differences between highly automated and human-driven vehicles.

To this end, the present study used four driving situations (within-subjects factor *scenario*) which automated vehicles of the first generation will be able to master independently. In these four driving situations, human drivers interacted twice with highly automated target vehicles and twice with other human-driven target vehicles (within-subjects factor *driving behavior*). Human driver reactions to highly automated vehicles at first contact were examined on the subjective level including ratings of perceived driving mode, perceived safety, and comfort as well as on the objective level including a driving data analysis to determine the level of safety-criticality in the interactions.

In addition, the present study aimed to explore the effect of an external labelling of automated vehicles (between-subjects factor *external labelling*) on human driver reactions to these vehicles. To determine the extent to which human driver reactions are affected by the external labelling and / or by actual behavioral differences, human drivers were assigned to one of three experimental groups. In the first group, automated vehicles had no external label, so all effects were based on differences in driving behavior. In the second group, the automated vehicles' current driving mode was labelled externally, so human drivers knew that these vehicles were highly automated. In order to check the extent to which the labelling itself raises expectations regarding automated driving behavior, a third group was introduced in which target vehicles were incorrectly labelled. Here, highly automated vehicles had no external label. This variation corresponds to the case where an automated vehicle that is generally capable of automated driving is operated by human driver. In contrast, human-driven vehicles were externally labelled as highly automated vehicles. This variation covers the case that automated vehicles without external label behave strangely from human driver's perspective as it is questionable whether automated driving behavior is within or outside the range of human driving behavior.

Following from these considerations, the present study examined the following research questions:

RQ 1: Are human drivers in mixed traffic able to distinguish highly automated vehicles from human-driven vehicles due to differences in driving behavior?

RQ 2: Do human drivers perceive interactions with automated vehicles in mixed traffic more frequently as safety-critical or unpleasant than interactions with other human drivers?

RQ 3: Are interactions between human drivers and highly automated vehicles in mixed traffic objectively more safety-critical for human drivers than interactions with other human drivers in surrounding traffic? If so, what behavior of highly automated vehicles is causing safety-criticality?

RQ 4: Is an external labelling of highly automated vehicles on the highway recommendable?

Regarding RQ 1 to RQ 3, it was hypothesized that differences in subjective ratings of perceived driving mode, safety, and comfort as well as the safety-criticality of interactions with target vehicles were based on actual differences in driving behavior rather than external labelling in the groups with none or correct labelling.

Based on previous literature (Fuest et al., 2020), it was hypothesized that human drivers may distinguish automated and human-driven vehicles based on actual differences in driving behavior rather than an external labelling (RQ 1). Moreover, human drivers may perceive the defensive driving style of automated vehicles as friendly and pleasant. Therefore, it was hypothesized regarding RQ 2 that human drivers may perceive the first contact with highly automated vehicles as pleasant and safe as interactions with human-driven vehicles. Regarding RQ 3, it was hypothesized that interactions with automated vehicles may be as safe as interactions with human-driven vehicles due to automated vehicles' rule-compliant behavior which may be anticipatable for human drivers. Regarding RQ4, it was hypothesized that an external labelling of highly automated vehicles is not necessary to identify an automated vehicle's driving mode correctly as previous literature has suggested that automated driving behavior may already be sufficient (Fuest et al., 2020).

6.2 Methods

6.2.1 Expert interviews

There are numerous open questions regarding human drivers' first contact with automated vehicles on the highway that needed be answered before conducting a driving simulator study investigating the described research questions.

Firstly, it is yet unknown where human drivers will first interact with automated vehicles on the highway, i.e. which driving situations these vehicles will be able to master without human intervention.

Secondly, it is yet unclear how Level 3 vehicles of the first generation will operate in interactions with human drivers. It can be assumed that automated vehicles will show more rule-compliant behavior than human drivers (see Appendix A). However, it is understudied whether human drivers in mixed traffic will be able to distinguish automated vehicles from human-driven vehicles only on the basis of driving behavior differences alone.

Thirdly, it is yet unknown how automated vehicles will look like and how easy it will be to identify them based on their external appearance and, in turn, distinguish these vehicles from human-driven vehicles. Currently, a large number of studies investigate external HMIs as a means of communication with human road users (e.g., Bengler, 2020; Rouchitsas & Alm, 2019; Schieben et al., 2019; see also Chapter 3.3). A broad variety of messages can be conveyed to human road users by means of an external labelling, e.g., the automated vehicle's current driving mode or its next driving maneuvers (see Schieben et al., 2019 for a review). First insights from previous research show that an external labelling of highly automated vehicles on the highway did not affect how human drivers behaved toward these vehicles or evaluated their driving behavior (Fuest et al., 2020).

In preparation of the present study, structured expert interviews were conducted in order to make substantiated assumptions on the described open questions regarding (1) relevant driving situations in mixed traffic on the highway, (2) automated driving behavior in these driving situations, and (3) automated vehicles' external appearance (see Appendix A). In total, *N* = 9 experts from university research (1), OEMs (4), and automotive suppliers operating in Germany (4) were interviewed. All experts surveyed were actively involved in research on vehicle automation and covered the fields of vehicle automation technology, driver assistance system development and human factors. The experts were assured that no company name would be mentioned.

To this end, an interview guideline was developed to identify relevant driving situations in which human drivers will have their first direct contact with highly automated vehicles when these vehicles are being launched on the market. For each identified driving situation, further questions were asked regarding what characteristic driving behavior human drivers could expect from highly automated vehicles, and to what extent automated driving behavior will probably differ from human driving behavior in the given driving situations. Since highly automated vehicles of the first-generation will presumably not be able to master all driving situations without human driver intervention, experts were asked to describe system limits and the corresponding driving situations in which these limits will presumably be reached. Finally, the experts were asked whether highly automated vehicles will be externally labelled and to what extent these vehicles will communicate with other human drivers in mixed traffic interactions.

All expert interviews were conducted orally and then transcribed. For each question, the answers of the various experts were then summarized in a comparative manner. These summaries were used as a basis for Study 1 in this chapter and Study 2 (see Chapter 7). The interview guideline and a detailed summary of the interviewees' responses on all questions are available in Appendix A. The following sections provide an overview of the summarized expert statements regarding (1) relevant driving situations in mixed traffic on the highway (see Chapter 6.2.1.1), (2) automated driving behavior (see Chapter 6.2.1.2), and (3) automated vehicles' external appearance (see Chapter 6.2.1.3). All expert interviews were conducted in mid-2018, and captured a snapshot of the state of development at that time which may now be further advanced.

6.2.1.1 Definition of driving scenarios

According to the experts, highly automated driving will first be available in isolated driving situations on selected stretches of highway where highly automated vehicles will be able to overtake slower vehicles independently. Also, driving in congested traffic will be possible.

According to the experts, however, there are a number of driving situations where a highly automated vehicle will send a take-over request to its passenger, including (1) construction sites, (2) highway junctions, (3) highway access and exit, and (4) sensor vision impairment. Construction sites can be a system limit as lane markings may be missing or dirty due to construction works. In this context, the experts argued that construction sites present highly automated driving functions with the additional challenge that the traffic routing may change in the construction process. Highway junctions can be a system limit depending on the complexity of their infrastructural features, i.e. the number of lanes and turnings in the junction. Although highly automated systems may be able master some less complex highway junctions independently, a system limit will be reached at complex highway junctions. This inconsistency of take-over requests may confuse passengers because they may have previously experienced that the automated system had mastered a less complex highway junction independently. To avoid confusion, some experts suggested that junctions should cause a take-over request every time until highly automated vehicles will be able to master all highway junctions regardless of the complexity of infrastructural features without human intervention.

Regarding highway accesses and exits, the experts stated that more testing is needed to include these driving situations in a Level 3 system. In the first generation of highly automated vehicles, passengers will activate the automated system after having accessed the highway, and deactivate the system before exiting the highway.

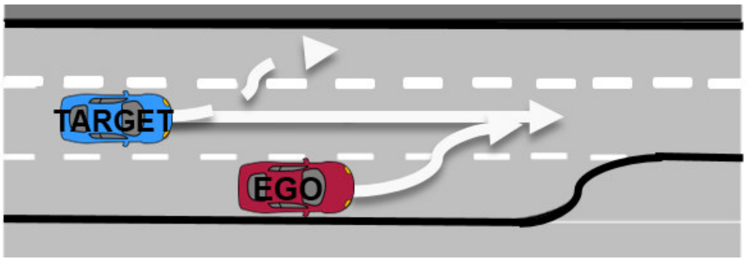
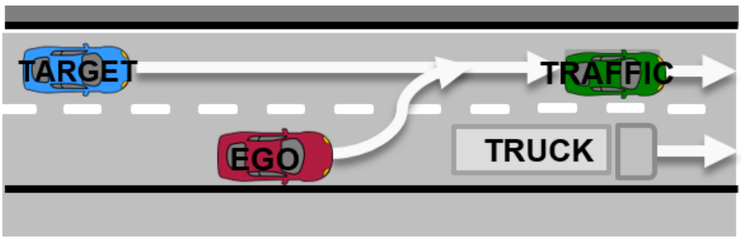
In case the sensors' vision is impaired due to extreme weather conditions including snow, or heavy rain, the vehicle will also send a take-over request to its passenger according to the experts.

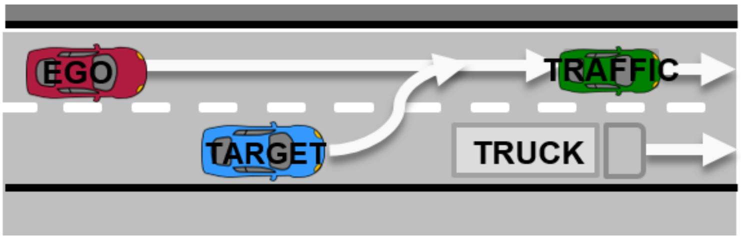
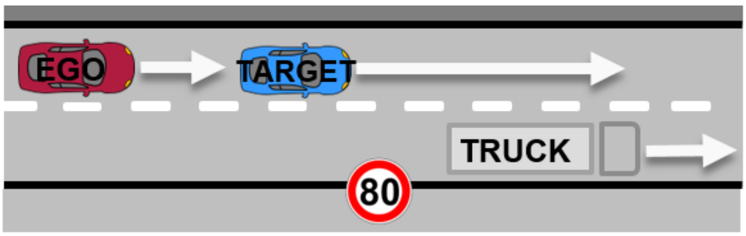
Based on the structured expert interviews, four driving situations were identified in which human drivers may interact highly automated vehicles in mixed traffic in the near future. A detailed description of all four examined driving situations is available in Table 1. These four driving situations included two different types of interactions between human drivers and target vehicles.

In the first type of interaction, target vehicles needed to react to human driving behavior. This type of interaction occurred in scenarios S01 (Highway access) and S02 (Lane change). In S01, a participant in the ego-vehicle changed from the acceleration lane to the right lane in front of a target vehicle in order to access the highway. In S02, a participant in the ego-vehicle changed lanes from the right lane to the left lane in front of a target vehicle.

In the second type of interaction, a participant in the ego-vehicle needed to react to the driving behavior of a lead target vehicle. This type of interaction occurred in scenarios S03 (Target vehicle changes lane) and S04 (Speed limit). In the first scenario, a lead target vehicle changed from the right lane to the left lane in front of the ego-vehicle in order to overtake a slow-moving truck (S03). The participant in the ego-vehicle needed to react by adapting speed to maintain a safe distance to the lead target vehicle during the overtaking maneuver. In S04, a lead target vehicle reacted to the introduction of the speed limit by reducing speed. The participant in the ego-vehicle needed to react to the lead target vehicle's behavior by maintaining a safe distance to the lead target vehicle. In the driving simulator study, each target vehicle interaction lasted one to three minutes.

Table 1 Description of the examined driving scenarios, including a description of the behavior of the human-driven and highly automated target vehicles.

Driving scenario	**Description**
Highway access (S01)	The participant in the ego-vehicle accelerates on the acceleration lane to access the highway. On the right lane, the target vehicle approaches from behind. The participant in the ego-vehicle merges in front of the target vehicle.  Human-driven target vehicle 1: The human driver in the target vehicle notices that the participant on the acceleration lane intends to change lanes. The human driver in the target vehicle therefore changes to the left lane to facilitate lane change for the participant in the ego-vehicle. Human-driven target vehicle 2: The human driver in the target vehicle notices that the participant on the acceleration lane intends to change lanes. The human driver in the target vehicle therefore accelerates in the right lane in order to impede the participant in the ego-vehicle from changing lanes. Highly automated target vehicle 1: As soon as the participant completed the lane change, the automated target vehicle maintains a minimum safety margin of 2.0 s time headway to the ego-vehicle. Highly automated target vehicle 2: As soon as the participant completed the lane change, the automated target vehicle maintains a minimum safety margin of 1.8 s time headway to the ego-vehicle.
Lane change (S02)	At 120 km/h, the participant in the ego-vehicle approaches a slow-moving truck (80 km/h) on the right lane, while the participant is overtaken by fast-moving cars on the left lane. On the left lane, there is a larger gap in front of the target vehicle which is large enough to overtake the slow-moving truck. The participant overtakes the truck and merges in front of the target vehicle.  Human-driven target vehicle 1: The human driver in the target vehicle drives on the left lane and maintains its speed. After the participant changes to the left lane, the target vehicle maintains minimum safety margin of 1.0 s time headway to the ego-vehicle Human-driven target vehicle 2: As soon as the participant starts the lane change, the human driver in the target vehicle accelerates in order to impede the participant from changing lanes. Highly automated target vehicle 1: The target vehicle drives on the left lane and maintains its speed. After the participant has completed the lane change, the target vehicle maintains a minimum safety margin of 2.0 s time headway to the ego-vehicle. Highly automated target vehicle 2: The target vehicle drives on the left lane and maintains its speed. After the participant has completed the lane change, the target vehicle maintains minimum safety margin of 1.8 s time headway to the ego-vehicle.

Driving scenario	Description
Target vehicle merges (S03)	The participant in the ego-vehicle drives at 140 km/h on the right lane, then changes to the left lane to overtake a line of slow-moving cars. Among these vehicles is a target vehicle which intends to overtake a slow-moving lead truck (80 km/h). The target vehicle overtakes the truck and merges in the left lane in front of the participant.  Human-driven target vehicle 1: The human driver in the target vehicle initiates the lane change as soon as it falls below a minimum safety margin of 1.2 s time headway to the slow-moving truck. Human-driven target vehicle 2: The human driver in the target vehicle initiates the lane change as soon as it falls below a minimum safety margin of 1.0 s time headway to the slow-moving truck. Highly automated target vehicle 1: The target vehicle initiates the lane change as soon as it falls below a minimum safety margin of 2.2 s time headway to the slow-moving truck. Highly automated target vehicle 2: The target vehicle initiates the lane change as soon as it falls below a minimum safety margin of 2.0 s time headway to the slow-moving truck.
Speed limit (S04)	The participant in the ego-vehicle drives at 120 km/h on the right lane and approaches a lead target vehicle, which the participant is instructed to follow at a safe distance. After a minute of follow-up drive on the right lane, the target vehicle and the participant in the ego-vehicle approach a slow-moving truck (80 km/h), and start to overtake by changing to the left lane. During the overtaking process, a speed limit of 80 km/h is introduced. When the overtaking process is completed, the speed limit is removed.  Human-driven target vehicle 1: As soon as the speed limit is introduced, the human driver in the target vehicle decelerates at 1.5 m/s^2 at the level of the sign and then maintains a speed of 85 km/h which is reached 125 m behind the road sign. When the speed limit is removed, the human driver in the target vehicle accelerates at 2.0 m/s^2 as soon as the sign is in sight, i.e. 125 m before the sign. Human-driven target vehicle 2: As soon as the speed limit is introduced by the road sign, the human driver in the target vehicle decelerates at 2.0 m/s^2 and then maintains a speed of 90 km/h which is reached 125 m behind the road sign. When the speed limit is removed, the human driver in the target vehicle accelerates at 2.5 m/s^2 as soon as the sign is in sight, i.e. 125 m before the sign. Highly automated target vehicle 1: The target vehicle already decelerates before the road sign with 1.5 m/s^2 and reaches the maximum permitted speed of 80 km/h shortly before corresponding the road sign. When the speed limit is removed, the target vehicle accelerates at 2.5 m/s^2 beginning at the sign. Highly automated target vehicle 2: The target vehicle already decelerates before the sign with 2.5 m/s^2 and reaches the maximum permitted speed of 80 km/h shortly before corresponding the sign. As soon as the speed limit is removed, the target vehicle accelerates at 2.5 m/s^2 beginning at the sign.

6.2.1.2 Definition of highly automated (and human) behavior in the driving scenarios

For the identified driving situations (see Table 1), the experts were asked about specific configurations of highly automated driving behavior which human drivers could expect from highly automated vehicles, and, to what extent this behavior would probably differ from human driving behavior. Experts agreed that highly automated driving behavior is characterized by strict adherence to traffic rules, e.g., maintaining maximum permitted speed, and following recommendations such as maintaining a safety margin of half a speedometer (1.8 s time headway) or more to the lead vehicle in a car-following situation (see ADAC, 2019; Vogel, 2003).

Comparing highly automated driving behavior and human driving behavior, the experts pointed out three potential key differences:

- If human drivers change lanes in front of a highly automated vehicle, a highly automated vehicle will maintain a large distance to the lead vehicle and slow down if necessary to maintain a safety margin of half a speedometer (approx. 1.8 s) or more.
- If highly automated vehicles approach a slower vehicle on their own lane, they will initiate the overtaking process at a considerable safety margin equivalent to half a speedometer (approx. 1.8 s) or more to the lead vehicle.
- In the case of speed limits, highly automated vehicles will be adhering strictly to the speed limit and the respective road signs. As a consequence, highly automated vehicles decelerate well before the speed sign and accelerate only after the speed limit is removed by the corresponding sign.

These characteristic differences between human and highly automated driving behavior regarding rule-compliance formed the basis of the behavior of human-driven cars and highly automated cars in the driving scenarios (S01 – S04) used in the present study.

According to the experts, highly automated vehicles can have manufacturer-specific driving styles within the legal framework, similar to the way human drivers display a wide range of driving styles (e.g., Sagberg et al., 2015; Taubman-Ben-Ari et al., 2004). The experts specified that *driving style* in the context of highly automated driving refers to specific technical configurations of driving behavior, e.g., differences in acceleration rates during lane change maneuvers. To include these differences in driving style between automated and human-driven vehicles in the present study, participants experienced each driving situation four times, twice with target vehicles being modelled after highly automated driving styles and twice with target vehicles modelled after human driving styles (see Table 1). Thus, it was possible to examine not only whether participants noticed differences in driving style but also to what extent these differences affected human driver reaction to highly automated vehicles in the four driving scenarios. In addition, this approach allowed for direct comparisons between automated and human driving behavior regarding human driver reaction in the examined driving scenarios.

Regarding human driving behavior, the initial idea was to conduct the present study as a linked simulator study with a human confederate driving in the human-driven target vehicles. However, one has to acknowledge the wide range of human driving styles in the selected driving scenarios (e.g., Sagberg et al., 2015; Taubman-Ben-Ari et al., 2004), which would have resulted in a huge variation of human-driven target vehicle behavior in the present study. Therefore, the idea of a linked simulator study was discarded. Instead, the two configurations of human driving behavior were chosen based on the expert interviews and everyday driving experience and implemented as simulated vehicles, just like the highly automated target vehicles. In doing so, the implemented configurations of human driving behavior included two prototypical configurations of human driving behavior, but no extreme configurations. This would have been beyond the scope of this dissertation.

In S01, the two highly automated target vehicles reacted to the lead ego-vehicles lane change by maintaining the recommended safety margin of at least half a speedometer (1.8 s time headway) or more (2.0 s time headway), whereas human-driven target vehicles changed to the left lane or accelerated to impede the lead ego-vehicle from the intended lane change. In S02, the highly automated target vehicles reacted to the ego-vehicles lane change by maintaining the recommended safety margin of at least half a speedometer (1.8 s time headway) or more (2.0 s time headway), whereas human-driven target vehicles maintained smaller safety margins (1.2 s / 1.0 s time headway). In S03, the highly automated target vehicles overtook the slower truck at larger safety margins of more than half a speedometer (2.2 s / 2.0 s time headway) to the lead truck compared human-driven target vehicles (1.2 s / 1.0 s time headway). In S04, the highly automated target vehicles reacted to the introduction of the speed limit by braking well before the sign to reach the maximum permitted speed of 80 km/h at the sign whereas human-driven target vehicles started braking at the sign and exceeded the maximum permitted speed (85 km/h / 90 km/h). For a detailed description of the configurations of target vehicle behavior in driving scenarios S01 to S04 see Table 1.

6.2.1.3 External labelling of highly automated vehicles

The experts agreed that external labelling of highly automated vehicles on the highway is subject to a controversial ongoing discussion within the research field of vehicle automation. Most of the experts' arguments were already mentioned in previous literature (see Chapter 3.3).

As an argument in favor of an external labelling, one expert argued that human drivers may be prepared to react if a highly automated vehicle showed any unexpected behavior. So, an external label may help human drivers to establish an adequate idea of the capabilities and system limits of highly automated systems.

As an argument against external labelling, the experts argued that it is unclear whether human drivers need additional information to master interactions with automated vehicles in mixed traffic successfully, and if so, what information an automated system should convey. According to the experts, the number of driving maneuvers on the highway is limited to acceleration and deceleration in longitudinal guidance as well as lane changes regarding lateral guidance because all vehicles travel into the same direction. For example, the intention to change lane is already indicated by using the indicators. In addition, the experts agreed that vehicle kinematics themselves can serve a visual cue for human drivers to understand the automated vehicle's intentions. According to the experts, it is therefore largely unclear how beneficial an additional external labelling would be for human drivers. Some experts even suggested that an additional external labelling might contribute to human drivers being suspicious or curious of this new type of vehicle, challenging highly automated vehicles by showing risky driving behavior.

Summarizing these arguments, there seems to be no imperative need to label highly automated vehicles on highways, according to the experts. This conclusion is in line with previous literature (see Fuest et al., 2020). So, one may argue that the legally required means of communication may be sufficient to inform human drivers, e.g., using the indicator to convey the intention to change lanes (Färber, 2016; Federal Ministry of Justice and Consumer Protection, n.d.-a, n.d.-b). However, the experts also acknowledged that more research is needed to evaluate potential benefits and risks regarding an external labelling of highly automated vehicles on the highway as a specific use-case for highly automated systems.

To include external labelling in the present study, highly automated vehicles were externally labelled by means of a blue light rectangle (see Figure 4), displaying their current highly automated driving mode to other drivers.

Figure 4 External labelling of a highly automated target vehicle (Photo: Doris Sonntag).

The light rectangle was chosen to enable clear 360° visibilities for human drivers in the ego-vehicle from all angles (see Stanton et al., 2020), especially in the ego-vehicle's rear-view mirror. Although the exact eHMI design in terms of color and shape was irrelevant to the research questions examined in Study 1, the color of the eHMI was chosen based on previous research (see Faas & Baumann, 2019; Werner, 2018).

6.2.2 Experimental design

The present study followed a 3 x 4 x 4 mixed design (external labelling x scenario x driving behavior). The experimental design comprised two within-subjects factors, target vehicle driving behavior and driving scenario. In each scenario, participants experienced four configurations of target vehicle driving behavior whereof two configurations were modelled after highly automated driving behaviors and two configurations were modelled after human driving behaviors. This approach allowed not only for the detection of differences between the two driving modes (automated vs. human-driven) but also between the two configurations of target vehicle driving behavior (automated 1 vs. automated 2; human-driven 1 vs. human-driven 2) within each driving mode. Participants experienced all four configurations of target vehicle behavior in four examined driving scenarios S01 to S04 (= 16 trials per participant; see Table 1) covering two types of mixed traffic interactions. In S01 and S02, target vehicles reacted to participants' driving behavior whereas in S03 and S04, participants needed to react to the target vehicles' driving behavior. The two types of interactions are therefore analyzed separately (see Chapter 6.2.7).

The between-subjects factor, external labelling, was varied threefold: no labelling, correct labelling, and incorrect labelling. The group without labelling served as a control group. In this group, none of the target vehicles were labelled. In the group with correct labelling, a blue rectangle (see Figure 4) served as a labelling for all automated target vehicles whereas human-driven vehicles had no external label. So, the external labelling referred to the target vehicle’s current driving mode in this group. In the group with incorrect labelling, human-driven vehicles were labelled as highly automated with the blue light rectangle while highly automated vehicles had no external label. This type of external refers to the vehicle’s general capability to drive automatically. This information can be ambiguous because a vehicle being generally capable of automated driving may still be operated by a human driver according to the definition of SAE Level 3 (SAE, 2014, 2018). So, it might be difficult to determine from a human driver’s outside perspective in mixed traffic whether the automated system or the human inside the automated vehicle is currently in charge of the driving task. This manipulation of external labelling also includes driving situations in which automated vehicles are not externally labelled but they still behave strangely. The experimental design is summarized in Table 2.

Table 2 Experimental study design and participants in the experimental groups.

<table>
<tr><th colspan="8">External labelling (between-subjects)</th></tr>
<tr><td colspan="6">No labelling
(N = 17)</td><td>Correct labelling
(N = 16)</td><td>Incorrect labelling
(N = 18)</td></tr>
<tr><td colspan="2"></td><td colspan="4">Scenario
(within-subjects)</td><td rowspan="6">Same as “no labelling”</td><td rowspan="6">Same as “no labelling”</td></tr>
<tr><td colspan="2">Driving behavior (within-subjects)</td><td>S01</td><td>S02</td><td>S03</td><td>S04</td></tr>
<tr><td rowspan="2">Automated</td><td>1</td><td></td><td></td><td></td><td></td></tr>
<tr><td>2</td><td></td><td></td><td></td><td></td></tr>
<tr><td rowspan="2">Human-driven</td><td>1</td><td></td><td></td><td></td><td></td></tr>
<tr><td>2</td><td></td><td></td><td></td><td></td></tr>
</table>

6.2.3 Driving simulator

The present study was conducted in a fixed-base driving simulator at the Department of Traffic and Engineering Psychology at Technische Universität Braunschweig (see Figure 5). The driving situations were created with the simulation software SILAB Version 6.0 (WIVW GmbH, https://wivw.de/de/; see also Krueger et al., 2005). The scenery was projected with three LCD projectors onto screens covering the driver’s field of view in the range of about 180°. The participants were seated in a seat box including driver and passenger seats and pedals at a distance of approximately 2.1 m from the screens. The rear-view mirror was projected as a rectangle onto the front screen. Separate screens were used to simulate mirrors and a speedometer. The experimenter monitored the test drive on six computer screens in an adjacent room. Driving data including current speed and position, as well as distances to target vehicles were recorded at a rate of 60 Hz.

Figure 5 Static driving simulator at the Department of Traffic and Engineering Psychology.

6.2.4 Dependent variables

To measure human driver reaction to highly automated vehicles in mixed traffic interactions, both questionnaire data and driving data were collected.

6.2.4.1 Perceived target vehicle driving mode

After each target vehicle interaction, participants were asked to rate driving behavior of the previously interacted with target vehicle (S01 / S02: *“Would you attribute the driving behavior of the lead vehicle rather to an automated vehicle or a human driver?”*, S03 / S04: *“Would you attribute the driving behavior of the subsequent vehicle rather to an automated vehicle or a human driver?”*) on a 5-point Likert scale from 1 (*automated*) to 5 (*human-driven*).

6.2.4.2 Perceived safety and comfort in target vehicle interactions

After each target vehicle interaction, participants rated perceived safety during the previous target vehicle interaction on an 8-point scale from 1 (*harmless*) to 8 (*unacceptable*) adapted from Neukum et al. (2008; see Figure 6) with the following instructions:

“Please look at the following scale and decide on a category (from harmless to Situation not acceptable) that best describes the previous situation. Please refine your judgment and tick the subcategory that best reflects your experience (very, medium or little).”

Situation not acceptable	
dangerous	**very**
	medium
	a little
unpleasant	**very**
	medium
	a little
harmless	

Figure 6 Perceived safety scale (adapted from Neukum et al., 2008).

In addition, participants rated perceived comfort (S01 / S02: “*How pleasant was the behavior the subsequent vehicle?*”, S03 / S04: “*How pleasant was the behavior the lead vehicle?*”) in the previous target vehicle interacted with on a 5-point Likert scale from 1 (*very unpleasant*) to 5 (*very pleasant*) after each target vehicle interaction.

6.2.4.3 Safety-criticality of target vehicle interactions

To analyze safety margins as indicators of safety-criticality in a driving situation, *time headway* is a widely used measurement. Time headway is defined as “the elapsed time between the front of the lead vehicle passing a point on the roadway and the front of the following vehicle passing the same point” (Evans, 1991, p. 313) in a car-following situation. On German roads, the general recommendation is to maintain a safety margin of half a speedometer (= 1.8 s time headway) to a lead vehicle in car-following situations on roads outside of urban areas (ADAC, 2019; Vogel, 2003). For safety margins smaller than half a speedometer (= 0.9 s time headway) to a lead vehicle, drivers are being fined for close following (ADAC, 2019; Vogel, 2003).

A second frequently used measurement of criticality is *time-to-collision* (TTC), also referred to as *time-measured-to-collision* (TMTC; Hayward, 1972). Hayward (1972, p. 27) defined time-to-collision as “the time required for two vehicles to collide if they continue at their present speeds and on the same path”. In contrast to time-to-collision, time headway does not take the speed differences of the two vehicles in a car-following situation into account (Vogel, 2003). This is of major advantage because time headway can be calculated in every car-following situation even if the speed of the subsequent vehicle is lower than the speed of the lead vehicle, i.e. if the two vehicles are not on an immediate collision course (Vogel, 2003). In this case, time-to-collision would be undefined (Vogel, 2003), although a collision might be imminent if the lead vehicle brakes unexpectedly.

Due to this limitation of the time-to-collision measure, time headway is used to measure the safety margins in the present study. In addition, the number of car-following situations resulting in close following (< 0.9 s time headway) were recorded. In the present study, all interactions between participants in the ego-vehicle and target vehicles occurred in such car-following situations.

In S01 and S02, participants in the ego-vehicle merged in front of a target vehicle. So, the following target vehicle needed to react to the preceding ego-vehicle's lane change. Here, the recorded minimum safety margins (as measured by time headway) are an indicator of the target vehicles' reactions to human driving behavior. Table 3 provides a description of the measures of the safety-criticality.

Table 3 Safety-criticality measures in the examined driving scenarios S01 and S02.

Scenario	Description	Measure
S01	A participant in the ego-vehicle accelerates on the acceleration lane to access the highway. On the right lane, the target vehicle approaches the ego-vehicle from behind. The participant in the ego-vehicle merges in front of the target vehicle.	At the time of the lane change: 1. Target vehicles' minimum time headway to preceding ego-vehicle During car-following: 1. Number of interactions with close following (< 0.9 s time headway)
S02	At 120 km/h, a participant in the ego-vehicle approaches a slow-moving truck (80 km/h) on the right lane, while the participant is overtaken by fast-moving cars on the left lane. On the left lane, there is a larger gap in front of the target vehicle, large enough to overtake the slow-moving truck. The participant overtakes the truck and merges in front of the target vehicle.	At the time of the lane change: 2. Target vehicles' minimum time headway to preceding ego-vehicle on the left lane During car-following: 3. Number of interactions with close following (< 0.9 s time headway)

In S03 and S04, participants in the ego-vehicle following a lead target vehicle needed to react to the lead target vehicle's lane change in front of the ego-vehicle (S03) or braking as a reaction to the introduction of the speed limit (S04). So, participants' minimum safety margins (as measured by time headway) to lead target vehicles are an indicator for participants' reaction to the driving behavior of the target vehicles in these two scenarios. Table 4 provides a description of the recorded measures of safety-criticality in S03 and S04.

Table 4 Safety-criticality measures in the examined driving scenarios S03 and S04.

Scenario	Description	Measure
S03	The participant in the ego-vehicle drives at 140 km/h on the right lane, then changes to the left lane to overtake a platoon of slow-moving cars. Among these vehicles is a target vehicle which intends to overtake a slow-moving lead truck (80 km/h). To overtake the truck, the target vehicle merges in front of the participant in the ego-vehicle.	During the overtaking process: 1. Participants' minimum safety margin (as measured by time-headway) to the lead target vehicle on the left lane During car-following: 2. Number of interactions with close following (< 0.9 s time headway)
S04	The participant in the ego-vehicle drives at 120 km/h on the right lane and approaches a target vehicle, which the participant is instructed to follow at a safe distance. After a minute of follow-up drive on the right lane, the target vehicle and the participant in the ego-vehicle approach a slow-moving truck (80 km/h), which both begin to overtake. During the overtaking process, a speed limit of 80 km/h is introduced.	During the overtaking process: 1. Participants' minimum safety margin (as measured by time-headway) to lead target vehicle at the introduction of the speed limit During car-following: 2. Number of interactions with close following (< 0.9 s time headway)

6.2.4.4 Evaluation of the external labelling

After completing the simulator study, all participants were asked to evaluate the external labelling of highly automated vehicles *("What is your attitude towards the idea of labelling automated vehicles?")* using 5-point scale from 1 (*very negative*) to 5 (*very positive*) in a final survey. Furthermore, participants were asked whether they had behaved or would have behaved differently in interactions with labelled vehicles (Correct / Incorrect labelling: *"Did you behave differently to the vehicles because of the labelling?"* / No labelling: *"Would you have behaved differently to the vehicles during the test drive if they had been labelled as automated vehicles?"*) using binary response format (yes / no). Participants could then specify how they had behaved differently in an open question format.

6.2.5 Procedure

Upon arrival, participants were acquainted with the experimental procedure and signed informed consent for the scientific use of their data. Participants were informed that they were free to drop out of Study 1 at any point without any disadvantages. Participants then completed the socio-demographic questionnaire, which included questions on mobility behavior, technical affinity, experience with driver assistance systems, and automated driving.

After completing the sociodemographic questionnaire, all participants were informed that there will be a mixed traffic on the highway in the future but participants received no detailed information on the target vehicles' configuration in the selected driving situations. This was done to ensure that participants' spontaneous reactions could be captured. Then, participants were instructed that they would experience interactions with both human-driven and highly automated vehicles in a total of four driving situations on the highway. All participants were informed that the aim of Study 1 was to examine how human drivers' reacted to highly automated vehicles in first contact on the highway.

Next, participants were given the chance to acquaint themselves with the experimental situation and driving in the driving simulator by means of a five-minute training drive, which was especially important for maintaining a certain speed level and lane keeping in the test drives. The training drive was not included in data analysis. After the training drive, each participant was randomly assigned to one of the three experimental groups. In the two experimental groups with *correct* and *incorrect labelling*, participants were informed about the *external labelling* of highly automated vehicles. Consequently, participants in the experimental group with *incorrect labelling* were deceived. Participants in this group were debriefed about the deception immediately after completing Study 1. The control group (*no labelling*) were informed that highly automated vehicles could not be distinguished from human-driven vehicles based on their external appearance.

Prior to each driving situation, all participants received a detailed description of the imminent driving situation including the driving maneuver to be performed, so participants could concentrate fully on the target vehicle behavior. Participants were instructed to perform the driving maneuvers only if they felt safe enough to do so. Furthermore, participants should avoid collisions with other vehicles as they would in real-world driving.

After each target vehicle interaction, participants were navigated to a highway parking lot, where participants were asked to rate the target vehicle's driving mode as well as perceived safety and comfort during the target vehicle interaction.

6.2.6 Participants

Fifty-six participants took part in Study 1. The datasets of $n = 5$ participants had to be discarded due to technical difficulties (4), and motion sickness (1). The final sample consisted of $N = 51$ participants aged 20 to 71 ($M = 34.9$ years, $SD = 15.1$ years, 22 female). On average, participants had their driving license for 18 years ($SD = 15.4$ years). 55 % of the participants stated that they drove at least several times a week. Another 18 % drove at least several times a month. 51 % of the participants reported driving more than 9000 km per year. 71 % of the participants had experience with driver assistance systems. Participants' technical affinity was $M = 3.80$ ($SD = 0.50$) on the 6-point ATI scale (Affinity for Technology Scale; Franke et al., 2019), with male participants scoring significantly higher on technical affinity than female participants ($t(49) = 2.34$, $p = .023$). Two thirds (67 %) of the participants had already gained experience in the driving simulator at least once. Participants' attitude towards automated driving was predominantly positive as 61 % stated that they had a rather or a very positive attitude towards automated driving whereas a minority of 6 % stated they were rather negative. 39 % of the participants had a neutral attitude towards automated driving.

A prerequisite for participation in the driving simulator study was a valid driving license. All participants had normal or corrected-to-normal vision. Data collection took place in February and March 2019 at the Department of Traffic and Engineering Psychology at Technische Universität Braunschweig. The experiment lasted approximately 2 hours per participant. Participation was reimbursed with 20 EURO. Undergraduate Psychology students at Technische Universität Braunschweig could choose between monetary reimbursement or course credit. Participants were recruited from an internal database and a student email list. The study was approved by the ethics committee of the Faculty of Life Sciences at Technische Universität Braunschweig.

6.2.7 Data analysis

As the four examined driving scenarios covered two types of mixed traffic interactions, the two types of interactions were analyzed separately. For each type of interaction (S01 / S02, S03 / S04) all four dependent variables, perceived driving mode, perceived safety, comfort, and safety margins (as measured by minimum time headway), were each analyzed by means of a three-way 3 x 4 x 2 (external labelling, driving behavior, scenario) mixed ANOVA with pairwise comparisons including the within-subjects factors driving behavior and scenario the between-subjects factor external labelling. In total, eight ANOVAs were calculated. The results are reported separately for each of the two types of interactions (S01 / S02, S03 / S04).

First, the questionnaire data was analyzed as described. Overall, questionnaire data from 816 target vehicle interactions (51 participants) were analyzed. There was no missing data in the analyses.

Next, the safety margins as indicators of safety-criticality were analyzed. At the same time, driving data served as a manipulation check of target vehicle behavior (see Table 1). If the manipulation of target vehicle driving behavior was successful, participants' minimum time headways to target vehicles would vary depending on the configuration of the target vehicles' driving behavior. In the present study, driving data from 816 target vehicle interactions (51 participants) were recorded. However, four participants across all experimental groups ($n_{\text{no labelling}}$ = 1, $n_{\text{correct labelling}}$ = 2, $n_{\text{incorrect labelling}}$ = 1) considered driving onto the highway in front of the accelerating target vehicle (human-driven 2) in S01 too dangerous. These participants accessed the highway after the target vehicle had passed them. This behavior complied with the instructions, because participants were instructed to drive onto the highway in front of the target vehicle only if they felt safe enough to perform this driving maneuver. The missing driving data of these four participants was replaced with the group means of the combination of factors to avoid a disproportionate loss of data. Finally, the evaluation of the external labelling was analyzed descriptively.

All reported means in Study 1 are presented with 95 % confidence intervals (CI). If the assumption of sphericity was violated, degrees of freedom were corrected using either a Greenhouse-Geisser correction ($\varepsilon < .75$), or a Huynh-Feldt-correction ($\varepsilon > .75$). For significant results of the ANOVAs, η^2_p is reported as an effect size. A significance level of $p \leq .05$ was adopted in all statistical tests. In all pairwise comparisons, a Bonferroni correction was applied. For results of all pairwise comparisons for the main effects of the factors driving behavior, and external labelling in scenarios S01 / S02 and S03 / S04, please refer to Tables B1 to B4 in Appendix B. For statistical data analysis IBM SPSS statistics 25 was applied.

6.3 Results

6.3.1 Target vehicles react to human driving behavior (S01 / S02)

6.3.1.1 Perceived driving mode

The statistical tests performed for the outcome variable perceived driving mode are reported in Table 5. Table 6 provides the mean values and standard deviations for this outcome variable. The three-way mixed ANOVA revealed a significant two-way interaction effect between the between-subjects factor external labelling, and the within-subjects factor driving behavior (see Figure 7) as well as significant main effects of the within-subjects factors scenario (see Figure 8) and driving behavior on perceived driving mode.

Table 5 Statistical tests (mixed ANOVA) for differences between experimental groups, driving behavior and scenario regarding the outcome variable perceived driving mode.

	F	*df*	*p*	η^2_p
D (Driving behavior)	26.7	3,144	**< .001**	.36
E (External labelling)	0.1	2,48	.887	
S (Scenario)	13.2	1,48	**.001**	.22
D x E	8.3	6,144	**< .001**	.26
D x S	1.5	6.0,144.0	.232	
E x S	0.5	2,144	.607	
D x E x S	0.3	5.9,140.4	.945	

***Note.* Significant p-values in bold.**

Table 6 Mean values and standard deviations including experimental groups, driving behavior and scenario regarding the outcome variable perceived driving mode.

External labelling	Driving behavior		Scenario S01	Scenario S02
No labelling (control group)	Automated	1	2.18 (1.24)	2.00 (1.23)
		2	2.88 (1.17)	2.12 (1.05)
	Human-driven	1	4.06 (1.03)	3.53 (1.42)
		2	3.71 (1.40)	3.76 (1.20)
Correct labelling	Automated	1	2.19 (0.91)	1.81 (0.83)
		2	2.88 (0.96)	1.94 (0.85)
	Human-driven	1	3.38 (1.46)	2.94 (1.06)
		2	4.56 (0.81)	4.50 (0.73)
Incorrect labelling	Automated	1	3.22 (1.31)	2.83 (1.25)
		2	3.17 (1.25)	2.72 (1.18)
	Human-driven	1	2.61 (1.61)	2.67 (1.46)
		2	3.28 (1.27)	3.17 (1.54)

Figure 7 shows the significant interaction effect between the within-subjects factor driving behavior and the between-subjects factor external labelling on perceived driving mode. In the control group without external labelling, perceived driving mode ratings approximately equaled to the label *rather human-driven* for the two human-driven configurations of driving behavior (human-driven 1: lane change, human-driven 2: accelerating). Perceived driving mode ratings differed for the two configurations of highly automated driving behavior. For the configuration automated 2 (1.8 s time headway), subjective ratings ranged between the labels *rather automated* and *undecided* whereas ratings of the configuration automated 1 (2.0 s time headway) approximately equaled to the label *rather automated.* Across all four configurations of target vehicle driving behavior, perceived driving mode ratings matched with the target vehicles' actual driving mode in the control group.

In the group with correct external labelling, in which the external labelling of the target vehicles corresponded to their current driving mode, perceived driving mode ratings of the two configurations of highly automated driving behavior were almost identical to the corresponding ratings in the control group. The configuration human-driven 2 was rated as *human-driven* in the group with correct external labelling, thus this configuration was rated more human-like than in the control group. However, ratings of the configuration human-driven 1 were more ambiguous, being rated more automated than in the control group.

In the group with incorrect labelling, the perceived driving mode ratings of all four driving behavior configurations were centered around the label *undecided.*

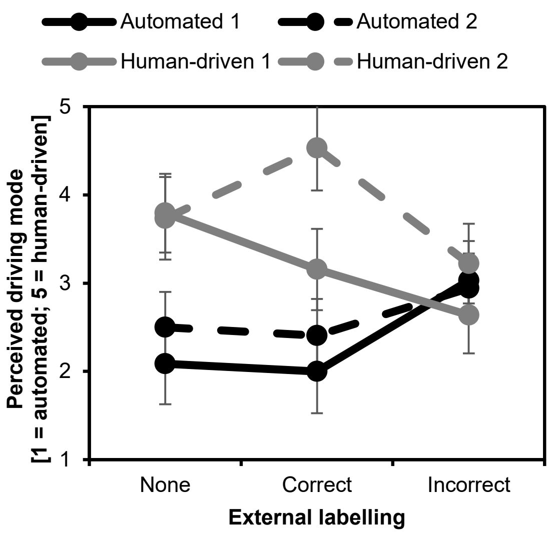


Figure 7 Perceived driving mode rating (means with 95 % CI) depending on driving behavior (D) and external labelling (E).

Regarding the significant main effect of the within-subjects factor driving scenario on perceived driving mode (see Figure 8), target vehicles were rated more human-driven in S01 (Highway access) compared to in S02 (Lane change) regardless of the configuration of driving behavior (M_{S01} = 3.18, M_{S02} = 2.83, p = .001).

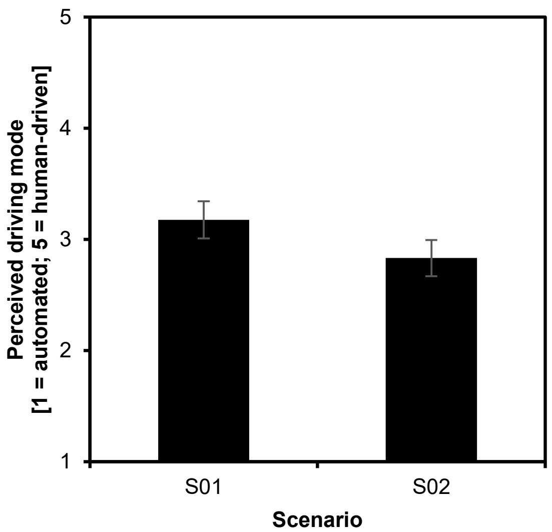


Figure 8 Perceived driving mode rating (means with 95 % CI) depending on scenario (S).

6.3.1.2 Perceived safety and comfort in target vehicle interactions

The statistical tests performed for the outcome variables perceived safety and comfort are reported in Table 7. The respective mean values and standard deviations are reported in Table 8. The three-way mixed ANOVAs revealed a significant two-way interaction effect between the within-subjects factors driving behavior and scenario on perceived safety (see Figure 9 left) and comfort (see Figure 9 right) as well as two significant main effects of driving behavior.

Table 7 Statistical tests (mixed ANOVA) for differences between experimental groups, driving behavior and scenario regarding the outcome variables perceived safety and comfort.

	Perceived safety				Comfort			
	F	*df*	*p*	η^2_p	*F*	*df*	*p*	η^2_p
D (Driving behavior)	65.7	2.8,134.9	**< .001**	.58	74.4	3,144	**< .001**	.608
E (External labelling)	1.0	2,48	.386		0.2	2,48	.852	
S (Scenario)	0.9	1,48	.350		1.0	1,48	.329	
D x E	1.6	6,144	.151		2.2	6,144	.051	
D x S	7.8	2.6,126.2	**< .001**	.14	12.8	3,144	**< .001**	.21
E x S	0.6	2,48	.544		0.1	2,48	.955	
D x E x S	0.8	5.3,126.2	.574		1.1	6,144	.391	

***Note.* Significant p-values in bold.**

Table 8 Mean values and standard deviations including experimental groups, driving behavior and scenario regarding the outcome variables perceived safety and comfort.

			Perceived safety		Comfort	
External labelling	Driving behavior		S01	S02	S01	S02
No labelling (control group)	Automated	1	2.94 (2.28)	1.59 (1.50)	3.12 (1.32)	3.94 (1.14)
		2	2.65 (2.37)	1.65 (1.50)	3.47 (1.33)	4.18 (1.02)
	Human-driven	1	1.06 (0.24)	1.76 (1.52)	4.76 (0.44)	4.00 (0.94)
		2	4.82 (2.38)	5.00 (1.73)	2.29 (1.26)	1.94 (0.97)
Correct labelling	Automated	1	1.56 (1.03)	1.63 (1.54)	4.13 (0.62)	4.13 (0.50)
		2	2.25 (1.39)	1.87 (1.50)	3.44 (1.03)	4.13 (0.81)
	Human-driven	1	1.19 (0.54)	2.25 (1.34)	4.69 (0.79)	3.69 (1.01)
		2	4.44 (1.75)	4.13 (2.03)	1.81 (0.98)	2.38 (1.03)
Incorrect labelling	Automated	1	2.39 (2.00)	1.39 (1.20)	3.78 (1.35)	4.33 (0.97)
		2	2.11 (1.53)	1.56 (0.71)	3.28 (1.32)	4.11 (0.68)
	Human-driven	1	2.33 (1.80)	2.22 (1.59)	4.39 (1.04)	3.33 (1.24)
		2	4.00 (2.20)	3.61 (2.00)	2.28 (1.36)	2.50 (1.30)

Figure 9 left shows the significant two-way interaction effect between the within-subjects factors driving behavior and scenario on perceived safety. In S01, the driving behavior of the target vehicle configuration human-driven 1 was rated as the safest of all four driving behaviors in this scenario as this configuration facilitated the highway access for participants in the ego-vehicle by changing to the left lane. Perceived safety ratings for this configuration equaled to the label *harmless*. It was followed by the two configurations of highly automated driving behavior maintaining large minimal safety margins (2.0 s / 1.8 s time headway) to the lead ego-vehicle. Perceived safety ratings for these two configurations were almost identical and approximately equaled to the label *a little unpleasant*. In contrast, perceived safety ratings of target vehicle human-driven 2 ranged between the labels *very unpleasant* and *a little dangerous* as the target vehicle accelerated to impede participants from accessing the highway. In S02, the two configurations of highly automated driving behavior were rated as the safest driving behavior maintaining large minimal safety margins (2.0 s / 1.8 s time headway) to the lead ego-vehicle. Perceived safety ratings for these two configurations were almost identical and ranged between the labels *harmless* and *a little unpleasant*. These were followed by the configuration human-driven 1 that maintained a smaller minimal safety margin (1.0 s time headway) behind the lead ego-vehicle on the left lane, being rated *a little unpleasant*. Again, the ratings of accelerating target vehicle configuration (human-driven 2) ranged between the labels *very unpleasant* and *a little dangerous*. Pairwise comparisons revealed that the configuration human-driven 2 (accelerating behind the ego-vehicle) was rated significantly more safety-critical compared to the other three driving behaviors in S01 and S02 (all $p < .001$; see Table B1 in the Appendix).

As can be seen in Figure 9 right, very similar patterns emerged for the subjective ratings of comfort for all four configurations of driving behavior in the two scenarios. The configuration human-driven 1 was rated the most pleasant of all four driving behaviors in S01, being rated between the labels *rather pleasant* and *very pleasant*. It was followed by the two configurations of highly automated driving behavior, being rated between *medium* and *rather pleasant*. The configuration human-driven 2 was rated *rather unpleasant*. In S02, the two automated configurations were rated the most pleasant, receiving almost identical mean ratings. The mean ratings approximately equaled to the label *rather pleasant*. These were followed by the configuration human-driven 1, being rated between *medium pleasant* and *rather pleasant.* The configuration human-driven 2 was rated *rather unpleasant*. Pairwise comparisons revealed that this configuration was rated significantly more unpleasant than the other three driving behaviors in S01 and S02 (all $p < .001$; see Table B1 in the Appendix).

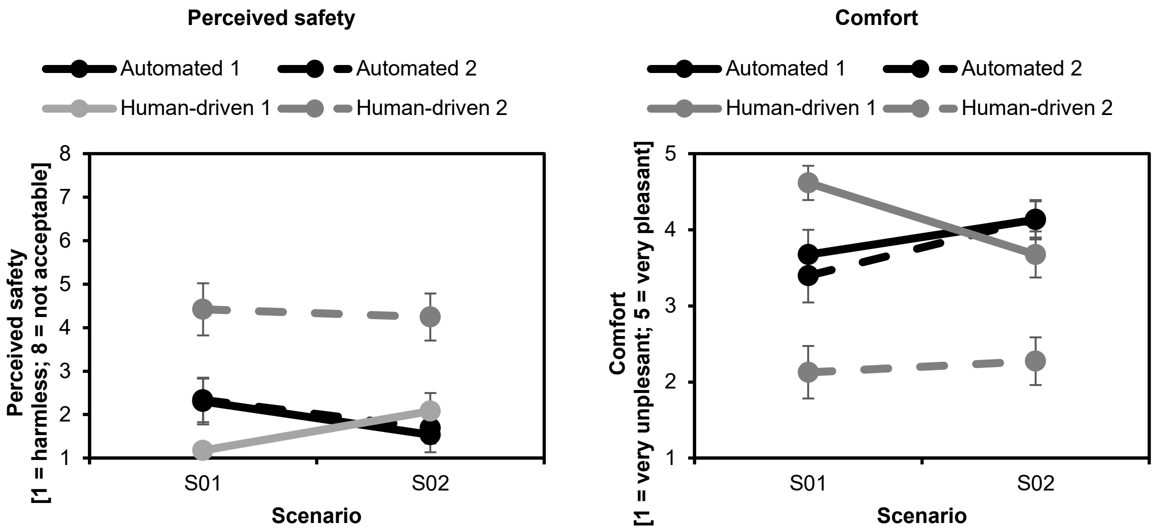


Figure 9 Left: Perceived safety rating (means with 95 % CI) depending on driving behavior (D) and scenario (S). Right: Comfort rating (means with 95 % CI) depending on driving behavior (D) and scenario (S).

6.3.1.3 Safety-criticality of target vehicle interactions

The statistical tests performed for the minimal safety margins (as measured by minimum time headway) are reported in Table 9 and the respective mean values and standard deviations in Figure 10. The three-way mixed ANOVA revealed two main effects of the within-subject factors driving behavior and scenario on the minimal safety margins (see Figure 10).

Table 9 Statistical tests (mixed ANOVA) for differences between experimental groups, driving behavior and scenario regarding the minimal safety margins.

	F	*df*	*p*	η^2_p
D (Driving behavior)	23.3	2.6,125.3	**< .001**	.33
E (External labelling)	0.5	2,48	.630	
S (Scenario)	4.4	1,48	**.040**	.09
D x E	1.5	6,48	.168	
D x S	0.6	2.6,125.7	.600	
E x S	1.6	2,48	.214	
D x E x S	1.0	6,144	.403	

Note. **Significant p-values in bold.**

Table 10 Mean values and standard deviations including experimental groups, driving behavior and scenario on the minimal safety margins. All means are reported in seconds.

External labelling	Driving behavior		Scenario S01	Scenario S02
No labelling (control group)	Automated	1	1.54 (0.69)	1.43 (0.32)
		2	1.68 (0.72)	1.43 (0.41)
	Human-driven	1	1.60 (0.51)	1.40 (0.24)
		2	1.08 (0.45)	1.32 (0.36)
Correct labelling	Automated	1	2.20 (0.49)	1.49 (0.24)
		2	1.73 (0.82)	1.50 (0.21)
	Human-driven	1	1.79 (0.64)	1.52 (0.24)
		2	1.20 (0.51)	0.86 (0.26)
Incorrect labelling	Automated	1	1.69 (0.73)	1.68 (0.79)
		2	1.53 (0.69)	1.46 (0.45)
	Human-driven	1	1.65 (0.72)	1.61 (0.48)
		2	1.13 (0.59)	1.03 (0.81)

Regarding the significant main effect of the within-subjects factor scenario, participants safety margins to the target vehicles were significantly larger in S01 (Highway access) compared to S02 (Lane change), thus interactions were significantly safer in S01 than in S02 from an objective point-of-view (M_{S01} = 1.57 s, M_{S02} = 1.39 s, p = .040; see Figure 10). However, almost all minimal safety margins were well above the threshold of 0.9 s time headway for close following in the two scenarios (see Table 10).

Regarding the significant main effect of the within-subjects driving behavior, pairwise comparisons revealed that minimal safety margins to target vehicles with the configuration human-driven 2 (accelerating vehicle) were significantly smaller than minimal safety margins to all other target vehicles in S01 and S02 (all p < .001, see Table B1 in the Appendix; see Figure 10). Participants' minimal safety margin to the configuration human-driven 2 ranged on average between 1.1 s in S01 and 1.4 s in S02 whereas minimal safety margins to the other three target vehicles ranged around 1.6 s to 1.8 s in S01 and between 1.4 s and 1.6 s in S02. As expected, participants in the ego-vehicle perceived interactions with the accelerating target vehicle as significantly more safety-critical compared to interactions with the other target vehicles that followed the ego-vehicle with pre-defined minimal safety margins.

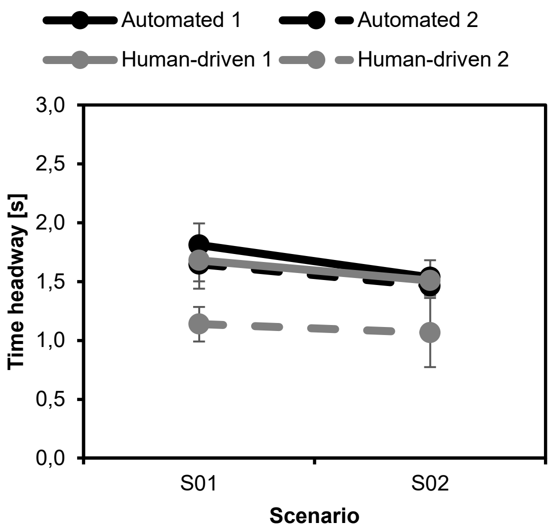


Figure 10 Minimal safety margins (as measured by minimum time headway; means with 95 % CI) depending on driving behavior (D) and scenario (S).

For further analysis of the safety-criticality, the number of interactions with close following was recorded for each target vehicle interaction (see Table 11).

In S01 (Highway access), 18 % (automated 1) and 22 % (automated 2) of all interactions with automated target vehicles resulted in close following. This finding indicates that some participants merged closely in front of the automated target vehicles, thus forcing the automated vehicles to brake in order to maintain their minimal safety margin of 2.0 s time headway (automated 1) and 1.8 s time headway (automated 2) to the ego-vehicle. In S02 (Lane change), only 4 % of the lane changes resulted in close following of automated target vehicles (automated 2). In the context, it should be noted, however, that the differential speed between participants in the ego-vehicle and the target vehicles was higher in S01 than in S02. Most interactions with close following occurred with the target vehicle configuration human-driven 2 (accelerating vehicle). 33 % of the interactions with this configuration were safety-critical in S01, and 59 % were safety-critical in S02.

Table 11 Number of safety-critical target vehicle interactions with close following (min. time headway < 0.9 s).

	Target vehicle driving behavior			
Driving scenario	Automated 1	Automated 2	Human-driven 1	Human-driven 2
S01	9 (18 %)	11 (22 %)	-*	17 (33 %)**
S02	0 (0 %)	2 (4 %)	1 (2 %)	30 (59 %)

Note. N **= 51 interactions per target vehicle in each driving scenario.**
***In S01, target vehicle human-driven 1 changed lanes, no close following could occur.**
****Missing data of n = 4 participants was not replaced (*n* = 47).**

6.3.2 Human drivers react to target vehicle behavior (S03 / S04)

6.3.2.1 Perceived driving mode

The statistical tests performed for perceived driving mode are reported in Table 12. Table 13 provides the mean values and standard deviations for this outcome variable. The three-way mixed ANOVA revealed two two-way interaction effects between the between-subjects factor external labelling and the within-subjects factor driving behavior (see Figure 11) as well as between the within-subjects factors diving behavior and scenario on perceived driving mode (see Figure 12). Furthermore, the analysis revealed main effects of driving behavior and scenario on perceived driving mode.

Table 12 Statistical tests (mixed ANOVA) for differences between experimental groups, driving behavior and scenario regarding the outcome variable perceived driving mode.

	F	*df*	*p*	η^2_p
D (Driving behavior)	23.5	2.9,138.4	**< .001**	.33
E (External labelling)	2.0	2,48	.150	
S (Scenario)	29.0	1,48	**< .001**	.38
D x E	6.7	6,144	**< .001**	.22
D x S	3.8	3,144	**.012**	.07
E x S	0.3	2,48	.710	
D x E x S	1.4	6,144	.211	

Table 13 Mean values and standard deviations including experimental groups, driving behavior and scenario regarding the outcome variable perceived driving mode.

External labelling	Driving behavior		Scenario S03	Scenario S04
No labelling (control group)	Automated	1	3.00 (1.23)	1.82 (1.13)
		2	3.82 (1.13)	2.06 (1.09)
	Human-driven	1	3.88 (0.99)	4.06 (1.30)
		2	3.88 (1.11)	3.76 (1.30)
Correct labelling	Automated	1	3.00 (1.37)	2.25 (1.18)
		2	3.12 (1.15)	2.19 (0.98)
	Human-driven	1	4.06 (1.00)	3.94 (0.93)
		2	4.38 (0.96)	4.06 (1.06)
Incorrect labelling	Automated	1	2.94 (1.16)	2.39 (1.38)
		2	4.00 (0.91)	3.06 (1.31)
	Human-driven	1	3.28 (1.27)	2.56 (1.42)
		2	3.67 (1.14)	2.78 (1.31)

Figure 11 shows the two-way interaction effect between the between-subjects factor external labelling and the within-subjects factor driving behavior. In the control group, perceived driving mode ratings approximately equaled to the label *rather human-driven* for the two configurations of human driving behavior (S03: 1.2 s / 1.0 s time headway; S04: 85 / 90 km/h) whereas the ratings of two automated configurations differed depending on the specific configuration. For the configuration automated 1 (S03: 2.2 s time headway; S04: 1.5 m/s^2 deceleration, 80 km/h at the speed sign), ratings ranged between the labels *rather automated* and *undecided* whereas ratings of the configuration automated 2 (S03: 2.0 s time headway; S04: 2.5 m/s^2 deceleration, 80 km/h at the speed sign) equaled to the label *undecided*.

In the group with correct labelling where the external labelling corresponded to the target vehicles' current driving mode, ratings of the configuration human-driven 1 were unchanged compared to the control group whereas the configuration human-driven 2 was rated more *human-driven* compared to the ratings in the control group. Furthermore, the external labelling affected the rating of the automated configurations. While the configuration automated 2 was rated slightly more automated compared to the rating in the control group, the configuration automated 1 was rated slightly more human-driven compared to the control group rating. Mean ratings of perceived driving mode ranged between the labels *rather automated* and *undecided* for both of the automated target vehicles.

In the group with incorrect labelling, perceived driving mode ratings of the two human-driven target vehicles were centered around the label *undecided.* Participants rated the configuration automated 2 more *human-driven* compared to the ratings in group with correct external labelling and the control group. The ratings of the configuration automated 2 ranged between the labels *undecided* and *rather human-driven.* In contrast, the ratings of the configuration automated 1 remained on the same level as in the group with correct labelling, and ranged between the labels *rather automated* and *undecided.*

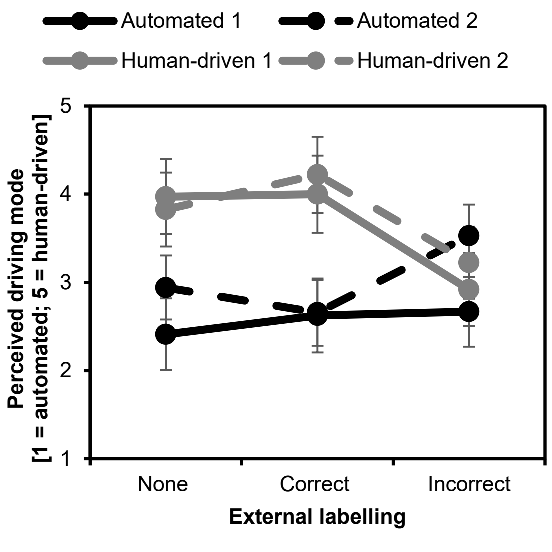


Figure 11 Perceived driving mode rating (means with 95 % CI) depending on driving behavior (D) and external labelling (E).

As can be seen in Figure 12, there was a significant interaction effect between the within-subjects factors scenario and driving behavior. In S03, the rating of configuration automated 1 (2.2 s time headway) approximately equaled to the label *undecided* whereas the ratings of the two human-driven configurations (1: 1.2 s time headway / 2: 1.0 s time headway) and the configuration automated 2 (2.0 s time headway) equaled to the label *rather human-driven*. In S04, the two configurations of human driving behavior (Human-driven 1: 85 km/h; Human-driven 2: 90 km/h) were rated *rather human-driven*, and the two automated configurations (1: 1.5 m/s^2 deceleration, 80 km/h at the speed sign; 2: 2.5 m/s^2 deceleration, 80 km/h at the speed sign) were rated *rather automated*.

Summing up, the general trend of perceived driving mode ratings matched better with the actual driving mode in S04 (Speed limit) than in S03 (Target vehicle merges).

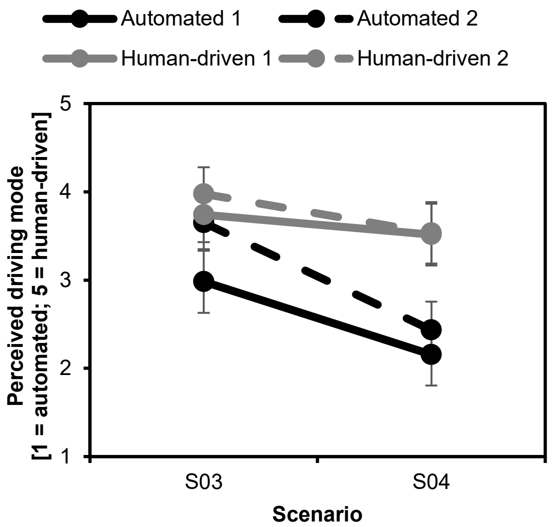


Figure 12 Perceived driving mode rating (means with 95 % CI) depending on driving behavior (D) and scenario (S).

6.3.2.2 Perceived safety and comfort

The statistical tests performed for perceived safety and comfort are reported in Table 14. Table 15 provides the mean values and standard deviations for these outcome variables. The analyses revealed significant two-way interaction effects between the within-subjects factors driving behavior and scenario for the two outcome variables (see Figure 13). Furthermore, there was a significant main effect of the within-subjects factor driving behavior on perceived safety whereas the main effect of driving behavior on the subjective ratings of comfort failed to become significant (p = .091).

Table 14 Statistical tests (mixed ANOVA) for differences between experimental groups, driving behavior and scenario regarding the outcome variables perceived safety and comfort.

	Perceived safety				Comfort			
	F	*df*	*p*	η^2_p	*F*	*df*	*p*	η^2_p
D (Driving behavior)	2.8	4.8,139.2	**.043**	.06	2.2	3,144	.091	
E (External labelling)	0.1	2,48	.878		0.1	2,48	.908	
S (Scenario)	1.5	1,48	.230		0.3	1,48	.867	
D x E	0.4	6,144	.864		1.1	6,144	.383	
D x S	10.4	3,144	**< .001**	.18	16.9	3,144	**< .001**	.26
E x S	0.9	2,48	.396		2.4	2,48	.106	
D x E x S	0.5	6,144	.782		0.9	6,144	.515	

Table 15 Mean values and standard deviations including experimental groups, driving behavior and scenario regarding the outcome variables perceived safety and comfort.

			Perceived safety		Comfort	
External labelling	Driving behavior		S03	S04	S03	S04
No labelling (control group)	Automated	1	2.06 (1.56)	3.06 (2.36)	3.82 (1.07)	2.59 (1.37)
		2	2.71 (2.11)	2.82 (1.55)	2.71 (1.26)	2.53 (1.01)
	Human-driven	1	2.35 (1.62)	2.88 (2.23)	3.24 (1.15)	2.41 (1.18)
		2	3.53 (1.74)	2.47 (1.91)	2.47 (0.87)	3.12 (1.17)
Correct labelling	Automated	1	2.75 (1.98)	2.62 (1.50)	3.00 (1.46)	2.56 (1.26)
		2	2.81 (1.94)	2.31 (1.58)	2.88 (0.96)	3.00 (1.10)
	Human-driven	1	3.37 (2.42)	2.56 (1.63)	2.44 (1.03)	3.06 (0.77)
		2	3.81 (2.23)	2.19 (1.64)	2.12 (0.96)	3.19 (1.11)
Incorrect labelling	Automated	1	2.06 (1.80)	3.12 (1.75)	3.61 (1.04)	2.50 (1.25)
		2	3.06 (1.96)	2.56 (1.63)	2.78 (1.26)	2.94 (1.06)
	Human-driven	1	3.28 (2.30)	2.78 (1.34)	2.50 (1.15)	2.67 (1.09)
		2	4.06 (2.07)	2.56 (1.58)	2.06 (1.06)	3.33 (0.91)

Figure 13 shows the interaction effect between the within-subject factors driving behavior and scenario on perceived safety and comfort. Overall, the perceived safety ratings ranged between the labels *a little unpleasant* and *very unpleasant* in S03 (see Figure 13 left). In this scenario, the configuration automated 1 (2.2 s time headway) was rated as the safest configuration, followed by automated 2 (2.0 s time headway), human-driven 1 (1.2 s time headway), and human-driven 2 (1.0 s time headway). So, the narrower the lane change of the lead target vehicle, the more dangerous the interactions were perceived by the participants in the ego-vehicle. In S04, perceived safety ratings were nearly identical for all four configurations of target vehicle driving behavior, with mean values being located in the mid-range of the scale.

Similar patterns emerged regarding comfort. In S03, the comfort ratings ranged between the labels *very unpleasant* and *rather pleasant* depending on the configuration of driving behavior. The configuration automated 1 (2.2 s time headway) was rated the most pleasant, followed by the configurations automated 2 (2.0 s time headway) and human driven 1 (1.2 s time headway) which were rated almost identically as neither pleasant nor unpleasant. The configuration human-driven 2 (1.0 s time headway) was rated as *rather unpleasant*. In S04 however, interactions with configuration human-driven 2 (90 km/h) were rated as more pleasant than interactions with other three configurations of driving behavior ($M_{\text{human-driven 2}}$ =

3.21). The mean ratings of the other three configurations were lower and located in the mid-range of the scale.

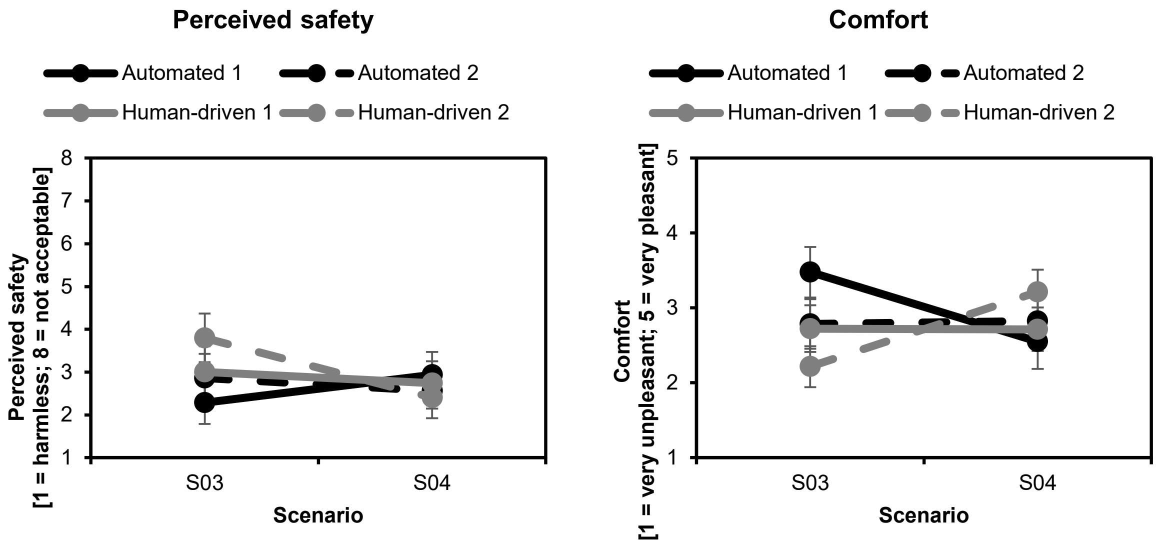


Figure 13 Left: Perceived safety rating (means with 95 % CI) depending on driving behavior (D) and scenario (S). Right: Comfort rating (means with 95 % CI) depending on driving behavior (D) and scenario (S).

6.3.2.3 Safety-criticality of target vehicle interactions

The statistical tests performed for the minimal safety margins (as measured by minimum time headway) are reported in Table 16. Table 17 provides the mean values and standard deviations for this outcome variable. The three-way mixed ANOVA revealed a significant two-way interaction effect between the within-subjects factors driving behavior and scenario (see Figure 14) as well as significant main effects of driving behavior and scenario on the safety margins.

Table 16 Statistical tests (mixed ANOVA) for differences between experimental groups, driving behavior and scenario on the minimal safety margins.

	F	*df*	*p*	η^2_p
D (Driving behavior)	19.4	2.7,128.4	**< .001**	.29
E (External labelling)	1.1	2,48	.344	
S (Scenario)	59.3	1,48	**< .001**	.55
D x E	0.8	2.7,144	.558	
D x S	15.6	2.7,129.9	**< .001**	.24
E x S	0.6	2,48	.570	
D x E x S	1.2	6,144	.326	

***Note.* Significant p-values in bold.**

Table 17 Mean values and standard deviations including experimental groups, driving behavior and scenario on the minimal safety margins. All means are reported in seconds.

External labelling	Driving behavior		Scenario S03	Scenario S04
No labelling (control group)	Automated	1	0.66 (0.36)	0.96 (0.28)
		2	0.72 (0.36)	0.93 (0.28)
	Human-driven	1	0.66 (0.34)	1.43 (1.07)
		2	0.77 (0.36)	1.79 (0.98)
Correct labelling	Automated	1	0.67 (0.46)	1.00 (0.48)
		2	0.63 (0.35)	0.97 (0.49)
	Human-driven	1	0.68 (0.51)	1.24 (0.61)
		2	0.67 (0.37)	1.42 (0.74)
Incorrect labelling	Automated	1	0.84 (0.51)	1.00 (0.59)
		2	0.73 (0.25)	1.30 (1.03)
	Human-driven	1	0.76 (0.50)	1.64 (0.93)
		2	0.80 (0.56)	1.96 (1.14)

As can be seen in Figure 14, participants' minimal safety margins to the lead target vehicle were nearly identical regardless of the target vehicles' configuration in S03. On average, participants' minimal safety margins to the lead target vehicle on the left lane ranged around 0.7 s time headway which is well below the threshold of 0.9 s time headway for close following. In S04, participants' minimal safety margins to the rule-compliant automated lead target vehicles were significantly lower than to the two configurations of human-driven target vehicles that exceeded the maximum permitted speed. This can be seen in the main effect of driving behavior. Mean values ranged around 1.0 s time headway for the two highly automated configurations, and between 1.4 s and 1.7 s time headway for the two human-driven configurations, with the latter two time headways corresponding to a little less than half a speedometer.

Regarding the significant main effect of the within-subjects factor scenario on the safety margins, the minimum time headways were significantly larger in S04 (Speed limit) compared to S03 (Target vehicle merges; $M_{S03} = 0.72$ s, $M_{S04} = 1.30$ s, $p < .001$). This finding is reflected by the minimal safety margins (as measured in time headway) shown in Figure 14.

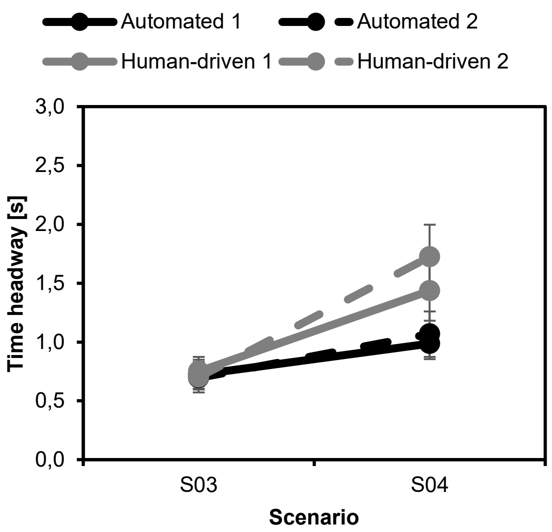


Figure 14 Minimal safety margins (as measured by minimum time headway; means with 95 % CI) depending on driving behavior (D) and scenario (S).

For further analysis of safety-criticality, the number of safety-critical interactions with close following was recorded for S03 (Target vehicle merges) and S04 (Speed limit; see Table 18). In S03, the majority of all interactions were safety-critical regardless of the configuration of target vehicle driving behavior (71 % – 82 % of all interactions). In S04, interactions with highly automated vehicles (automated 1: 49 %, automated 2: 49 %) were more often safety-critical compared to interactions with human-driven target vehicles (human-driven 1: 27 %, human-driven 2: 22 %). These findings are in line with the previously reported results on the minimal safety margins to the target vehicles (see Figure 14).

Table 18 Number of safety-critical target vehicle interactions with close following (minimum time headway < 0.9s).

	Target vehicle driving behavior			
Driving scenario	Automated 1	Automated 2	Human-driven 1	Human-driven 2
S03	40 (78 %)	36 (71 %)	38 (75 %)	42 (82 %)
S04	25 (49 %)	25 (49 %)	14 (27 %)	11 (22 %)

***Note.* *N* = 51 interactions per target vehicle in each driving scenario.**

6.3.3 Evaluation of the external labelling

After completing the simulator drives, participants evaluated the idea of labelling highly automated vehicles in a final survey. As can be seen in Figure 15, the obtained results from the evaluation differed depending on the type of external labelling participants had experienced previously in the simulator drives. In the control group without labelling, a majority of 12 (71 %) participants were in favor of the idea to label highly automated vehicles, whereas a minority of only 2 (12 %) participants considered the idea of labelling highly automated vehicles as a bad idea, and 3 (18 %) participants had a neutral attitude towards the idea of labelling highly automated vehicles. In the control group, 7 (41 %) participants also stated that they would have preferred labelled highly automated vehicles during the previous simulator drive.

In contrast, the obtained results from the evaluation in the group with correct labelling, where labelling referred to the current driving mode of a vehicle, were ambiguous. While 8 (52 %) participants rated the idea of labelling as good or very good, 6 (38 %) participants rejected a labelling. 5 (31 %) participants in this group were undecided regarding their labelling preference.

In the group with incorrect labelling, 9 (50 %) participants had a positive attitude towards labelling whereas 5 (28 %) participants rejected a labelling. 4 (22 %) participants in this group were undecided.

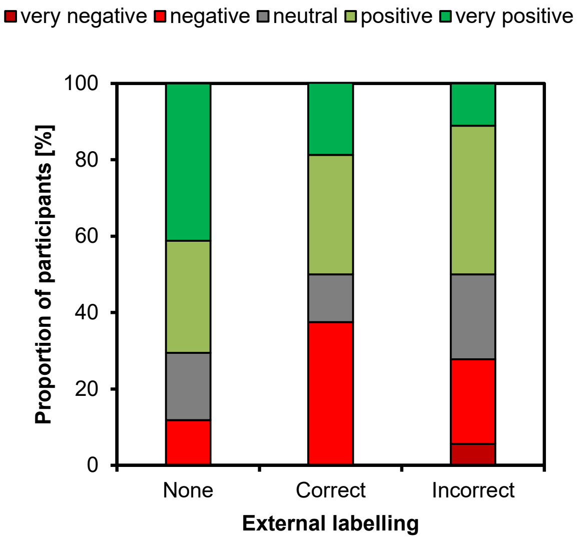


Figure 15 Evaluation of the external labelling depending on the experimental group (no labelling, correct labelling, incorrect labelling) in the final survey.

Furthermore, participants were asked whether they had behaved differently towards highly automated target vehicles than towards human-driven target vehicles due to the external labelling. As the results of the final survey showed, a majority of participants (n = 29) in the groups with correct or incorrect labelling in the test drive stated that they had not behaved differently towards the labelled vehicles (correct labelling: 63 %; incorrect labelling: 78 %).

Among the 22 participants (correct labelling: 38 %; incorrect labelling: 22 %) who stated they had behaved differently towards the labelled target vehicles, 8 (36 %) participants stated that they had driven more carefully, 7 (32 %) participants considered highly automated driving behavior to be more predictable due to the external labelling and 4 (18 %) participants stated that they themselves were more willing to take risks.

However, the analysis of the driving data provided no evidence that these participants had actually behaved differently towards labelled vehicles than the other participants who stated they had not changed their behavior due to the external labelling.

6.4 Discussion

The present study examined human driver reactions to highly automated vehicles at first contact on the highway. The focus was on the external distinguishability of highly automated and human-driven vehicles in mixed traffic and on human drivers' perceived safety and comfort as well as the safety-criticality of mixed traffic interactions. Human driver reactions in mixed traffic interactions were examined depending on the type of external labelling of the highly automated vehicles (no labelling, correct labelling, incorrect labelling) and four configurations of driving behaviors (automated 1, automated 2, human-driven 1, human-driven 2) in four selected driving scenarios (S01 – S04) that covered two types of interactions between human drivers and highly automated vehicles. In S01 (Highway access) and S02 (Lane change), target vehicles reacted to participants' driving behavior and vice versa in S03 (Target vehicle merges) and S04 (Speed limit). In the following, the results of the present study are discussed separately for the two types of interactions.

6.4.1 Target vehicles react to human driving behavior (S01 / S02)

In S01 and S02, the two highly automated target vehicles reacted to the human driving behavior by maintaining large safety margins to participants in the ego-vehicle (1.8 s / 2.0 s time headway). Regarding the driving behavior of human-driven target vehicles, a friendly (S01: lane change to the left lane, S02: 1.0 s time headway) and a progressive driving style (S01 & S02: acceleration behind ego-vehicle) were implemented to cover a certain range of human driving behavior. In the two driving scenarios, participants correctly identified large safety margins to preceding vehicles as a key feature of highly automated driving behavior if target vehicles had none or a correct label. In line with the hypothesis (RQ 1), human drivers were mostly able to distinguish between highly automated vehicles and human-driven vehicles based on behavioral differences, as suggested by previous literature (see Fuest et al., 2020). So, human drivers seem to have an adequate idea of how highly automated vehicles typically react in this type of interaction with human drivers. Whether this adequate idea was based on a correct situation model (see Endsley, 1995a) can only be speculated at this point. More detailed questionnaires and post-trial interviews would have been necessary to determine what the drivers' situation model was composed of and how complete the model was for the examined driving situations (for more background on the measurement of situation awareness see Endsley, 1995b). Also, it was not the aim of the present study to analyze drivers' situation model in depth, but rather to capture human drivers' spontaneous reaction to highly automated vehicles during first contact.

So, it can be concluded for this type of dyadic interaction where target vehicles react to human driver behavior that driving behavior is already a sufficient visual cue for human drivers to identify and distinguish highly automated vehicles from human-driven vehicles in mixed traffic. At the same time, this finding indicates that human drivers did not benefit from an additional external labelling of the current driving mode as the labelling failed to facilitate external distinguishability of highly automated and human-driven target vehicles (see Figure 7). An external labelling of the general capacity to drive automatically as in the experimental group with incorrect labelling led to confusion among human drivers. Based on this finding, it could be speculated that this confusion may have a negative impact on human drivers' acceptance of these vehicles in the long run. Therefore, labelling highly automated vehicles' general capacity to drive automatically is not recommendable.

Regarding perceived safety and comfort, human drivers rated the interactions with highly automated target vehicle at least as safe and comfortable as interactions with human-driven target vehicles (see Figure 9). This finding confirms the hypothesis (RQ 2) that human drivers in mixed traffic perceive the rule-compliant and defensive highly automated driving behavior as friendly and safe. In contrast, participants' perceived safety and comfort ratings of the two human-driven target vehicles depended on the specific configuration of driving behavior. Ratings for the defensively-driving configuration human-driven 1 were similar to the ratings of the highly automated target vehicles in S02, or even more positively in S01. Based on the unambiguously positive ratings of human-driven in S01, performing a lane change to support a human driver in the lead vehicle to access the highway appears to be the ideal reaction to the participant in the ego-vehicle in S01. Based on this finding, one may argue that a lane change would be a desirable reaction for highly automated vehicles in this situation. However, based on the expert interviews conducted in advance of the present study (see Appendix A), it remains questionable whether highly automated vehicles would perform a lane change in this driving scenario as highly automated driving behavior was being described as rather reactive, and besides, every lane change may at least in theory entail an inherent risk of a collision with another vehicle.

In contrast to the positive ratings of the human-driven 1 target vehicle, human drivers perceived the accelerating target vehicle (human-driven 2) as dangerous and rather unpleasant in the two driving scenarios. These contrasting findings for the two configurations of the human-driven target vehicles indicate that the specific configuration of driving behavior is a more important factor for human drivers' subjective ratings of perceived safety and comfort than the driving mode of a target vehicle.

Moreover, an external labelling (RQ 4) had no positive effect on the subjective ratings of perceived safety and comfort, which is in line with results from previous research in similar driving environments (e.g., GATEway project, 2017; see also Fuest et al., 2020). At the same time, previous research also showed that external HMIs enhanced perceived safety in pedestrian interactions with highly automated vehicles in urban areas (e.g., Böckle et al., 2017; De Clercq et al., 2019; Faas et al., 2020; Habibovic et al., 2018). These seemingly contrasting findings can be explained by the different driving environments and specific interactions (seeing the target vehicle in the rear-mirror vs. crossing situations). It can be assumed that implicit cues, i.e. vehicle kinematics are more important for interactions in the highway driving environment than explicit communication (see de Ceunyck et al., 2013, and Powelleit et al., 2018 for definitions of implicit / explicit communication cues). Therefore, it can be concluded that vehicle kinematics, i.e. actual driving behavior, is more relevant for drivers' perceived safety and comfort than the external appearance of highly automated vehicles in the examined highway driving situations.

Regarding the aspect of safety-criticality (RQ 3), the defensive driving behavior of the two highly automated target vehicles (> 1.8 s time headway) resulted in safe interactions with human drivers in mixed traffic (see Table 11). As hypothesized, interactions were similarly safe as or safer than interactions with the two human-driven target vehicles, depending strongly on the specific configuration, but not on external labelling (see Figure 10). While the minimal safety margins to the defensive human-driven target vehicle (human-driven 1) were located in a similar range as the minimal safety margins to the two highly automated target vehicles in S01 and S02, interactions with the target vehicle showing a more progressive configuration of human driving behavior (human-driven 2) were safety-critical (< 0.9 s) in some cases (S01: 34 %, S02: 59 %). This finding again shows that the driving mode of a vehicle in itself is not decisive as to whether an interaction is safety-critical, but rather the specific configuration of driving behavior. From a methodology-driven perspective, these findings point out that the manipulation of driving behavior was successful in the two driving scenarios (see Table 10).

Moreover, it is noteworthy that highly automated vehicles' minimal safety margins to human drivers in the lead ego-vehicle were sometimes smaller than the pre-defined safety margins of 1.8 s or 2.0 s time headway (see Figure 10). Obviously, some participants performed narrow lane changes, forcing the highly automated vehicles to brake in order to restore the pre-defined minimum safety margin to the lead ego-vehicle. This finding might fuel concerns from previous literature (e.g., Connor, 2016; Eliot, 2019; Stanton et al., 2020) that human drivers might take advantage of the rule-compliant highly automated driving behavior and merge closely in front of the automated vehicle. It is more likely, however, that participants may have had difficulties to estimate distances correctly in the simulated driving environment, tending to overestimate time-headways. In addition, the instructions may have contributed to some narrow lane changes, as participants were instructed to perform the lane change in front of the target vehicles (if they felt safe enough to do so). It is possible that most participants were so eager to follow the instructions that they accepted small safety margins to the target vehicle. Whether drivers would have carried out the lane changes in their own vehicles in real traffic can only be speculated. In total, $n = 4$ participants chose to stay on the acceleration lane in S01 instead of changing onto the right lane in front of the target vehicle because they considered the maneuvers to be too dangerous.

Summing up, the present study showed that human drivers were able to distinguish highly automated vehicles from human-driven vehicles in S01 and S02. Furthermore, interactions with automated vehicles are more safety-critical than interactions with human drivers in S01 and S02. This is in line with the subjective ratings of perceived safety and comfort. An external labelling of the current driving mode has no benefit for human drivers beyond being of mere informational value to human drivers.

6.4.2 Human driver react to target vehicle driving behavior (S03 / S04)

In the second type of interaction where human drivers needed to react to the driving behavior of a preceding target vehicle included a lane change (S03), and the introduction of a speed limit (S04). Regarding the external distinguishability of automated and human-driven target vehicles (RQ 1), the ratings of perceived driving mode were highly dependent on the driving scenario (see Figure 12). In S03, the two automated target vehicles changed lanes at a rather large safety margin to the preceding truck (2.2 s / 2.0 s time headway). Since this kind of driving behavior is also typical for human drivers, the configurations of highly automated driving behavior were rather within the range of human driving behavior in this driving scenario. Unlike in the study by Stanton et al. (2020), the simulated target vehicles behaved identically during the overtaking process in this study regardless of their driving mode (human-driven vs. automated). Thus, drivers could not have detected any differences between human and automated driving behavior in S03, although even existing differences may be difficult to detect from an external perspective (see Stanton et al., 2020). Taken together, this may explain why drivers have rated the two configurations of automated driving behavior as *undecided* and *rather human-driven*, being similar to the ratings of the two human-driven target vehicles (see Figure 12; see Table 13).

An alternative explanation for these indistinct ratings of perceived driving mode is that participants may have expected a different driving behavior from the highly automated vehicles, e.g., to continue driving behind the truck on the right lane to avoid any possibility of a safety-critical interaction with the ego-vehicle on the left lane (see Josten et al., 2019).

At the same time, it should be mentioned that it is difficult to estimate distances in the simulated driving environment correctly so that differences of up to 1.0 s time headway between the target vehicles were hardly noticeable for human drivers. However, choosing an even larger minimal safety margin (> 2.2 s time headway) for the configuration of the highly automated target vehicles would have been unrealistic as highly automated vehicles would only change lanes if necessary (see Appendix A). Another alternative explanation for the less distinct driving mode ratings could be that human drivers may have expected the two human-driven target vehicles reach higher speeds (> 120 km/h) during in the overtaking process, exceeding the speed limit.

In S04, the highly automated vehicles braked early before the speed sign, reaching the target speed at the sign and accelerated only when the speed limit was removed again whereas human-driven target vehicles first started to brake at the speed sign and accelerated before the speed limit was removed. Most participants identified the strictly rule-compliant driving behavior of the automated target vehicles correctly, with mean ratings approximately equaling to the label *rather automated* in the group with correct labelling and the control group. In contrast, deviations from traffic rules, i.e. by exceeding the maximum permitted speed, were correctly assigned to human driving behavior (see Figure 12; see Table 13). This finding suggests that participant expected correctly that highly automated vehicles would adhere very closely to traffic rules (see Appendix A) while human driving behavior can deviate more strongly from these rules. So, human drivers have an adequate idea of how highly automated vehicles would behave upon the introduction of a speed limit.

In comparison to S03, it was easier for human drivers to distinguish highly automated vehicles from human-driven vehicles in S04. Based on this finding, it could be speculated that forward compatibility (van Loon & Martens, 2015) is indeed situation-dependent, being easier to achieve in driving situations where highly automated driving behavior is rather close to or within the range of human driving behavior, such as in S03. In S04, however, automated driving behavior was clearly outside of the range of human driving behavior, lowering forward compatibility. In this context, an external labelling of the current driving mode failed to support human drivers in distinguishing highly automated driving behavior from human driving behavior. In contrast, an incorrect labelling led to confusion. These findings are in line with the results from S01 and S02, supporting the notion that drivers did not benefit from the additional eHMI – at least in the examined driving scenarios.

Regarding perceived safety and comfort (RQ 2), participants' ratings varied as a function of the target vehicles' minimal safety margins (as measured in time headway) to the preceding truck when starting the lane change in S03 (see Figure 13). The larger the time headway at lane change onset, the safer and the more pleasant human drivers rated the interaction regardless of the external labelling. This is in line with the hypothesis that interactions with highly automated vehicles are rated as safe and as pleasant as interactions with human-driven vehicles. In S04, the safety and comfort ratings were nearly identical regardless of the configurations of target vehicle driving behavior, although it is interesting that the different configurations of target vehicle driving behavior had almost no effect on the ratings. Only the interaction with the target vehicle human-driven 2, whose driving behavior rated the most *human-like*, was rated slightly more pleasant than the other three target vehicles (see Figure 13). Taken together, however, these results are in line with the hypothesis that human drivers perceived interactions with highly automated vehicles as safe and as pleasant as interactions human-driven target vehicles.

Regarding the aspect of safety-criticality (RQ 3), participants' safety margins to the four target vehicles were almost identical in S03, with 71 % to 82 % of all interactions being safety-critical (< 0.9 s minimum time headway; see Table 18). As described, it is possible that participants had either expected target vehicles to reach higher speeds (> 120 km/h) in the overtaking process, or to continue driving behind the truck on the right lane. As consequence, participants in the ego-vehicle may have misjudged the driving behavior and/or the speed of the preceding target vehicles. At the same time, the minimum time headway captures only a snapshot of the most safety-critical moment of an interaction, having only limited predictive value about whether a collision is imminent (see Vogel, 2003).

In S04, highly automated driving behavior was strictly rule-compliant (reaching the maximum permitted speed at the sign, exact adherence to speed, acceleration only as soon as the limit was removed). Presumably, participants were unfamiliar with this strict rule-compliance of highly automated vehicles resulting in short minimum time headways to preceding highly automated vehicles – at least for a few seconds. So, highly automated driving behavior caused an unwanted “surprise effect” for human drivers here. In the present study, this surprise effect was, however, not diminished by the external labelling of the current driving mode. Taking up the aspect of building a mental model of the capabilities and system limits of automated systems (e.g., Beggiato & Krems, 2013; Beggiato, Pereira et al., 2015; Blömacher et al., 2018, 2020; Forster et al., 2019, 2020), an external labeling may be recommendable to support this process in the longer run. An external labeling (RQ 4) referring to an automated vehicle's current driving mode may help to mitigate such "surprise effects" for human drivers in similar situations where a highly automated vehicle unexpectedly brakes to comply with traffic rules or displays other types of defensive or unexpected and unanticipated driving behavior human drivers are unfamiliar with as of yet (see Nyholm & Smids, 2020). In this context, previous research has also highlighted the aspects of training and educating passengers as users of automated systems to establish adequate mental models of an automated system (see Forster et al., 2020). Based on the obtained results in S04, it might be useful if education and training were not limited to passengers only, but also included human drivers in mixed traffic in order to maintain traffic safety. In this way, human drivers would be supported in forming “expectancies based on their internalized and consolidated understanding and experience with the vehicle mix (i.e. mental models of the system)” (Noy et al., 2018, p. 75). However, further research is needed to explore the benefits of an external labelling for human drivers in repeated mixed traffic interactions.

6.5 Limitations

The results obtained in the present study are subject to a number of limitations. Firstly, participants had no previous experience with highly automated vehicles or driving in mixed traffic prior to the simulator drives in the present study. In this respect, the approach of the present study corresponded to the realistic situation human driver will be confronted with when they first interact with highly automated vehicles on the highway in real-world driving. From the user perspective, a focus group study by Josten et al. (2018) showed that expectations of automated driving behavior may differ among drivers with little knowledge on driving assistance systems, resulting in a potential discrepancy between expectations and an automated system’s actual functionality as the automated function may operate differently than expected. This may also cause issues in first contact as human drivers may have different ideas about highly automated driving behavior as well. So, it can only be speculated whether and to what extent prior information on automated system functionality would have had changed subjective ratings of perceived safety and comfort or supported the external distinguishability between automated and human-driven vehicles in the present study.

Secondly, it was not possible to implement the entire spectrum of highly automated and human driving behavior facets in the present study. Instead, driving behavior implementations were limited to a few selected configurations to answer the research questions of whether human drivers are able to notice differences in the driving behavior of surrounding vehicles in mixed traffic at all, how human drivers perceive these behavioral differences, and whether human driver interactions with highly automated vehicles result in safety issues. To make substantiated assumptions on automated driving behavior, expert interviews were conducted in preparation of the present study (see Chapter 6.2.1). Automated vehicles of the first generation will presumably show very defensive driving behavior, i.e. minimal safety margins of at least half a speedometer (= 1.8 s time headway) or more and strict rule-compliance to the traffic rules. However, it is questionable whether these defensive configurations would be realistic in dense real-world traffic. Accordingly, the configurations used in the present study are an approximation to automated and human driving behavior in real-world driving.

Thirdly, participants experienced automated driving behavior only in a few short vehicle interactions lasting between one to three minutes each. So, it is unclear how human drivers perceive highly automated vehicles in mixed traffic beyond first contact. In addition, the number of examinable driving scenarios was per se limited, because experts agreed that automated vehicles of the first generation will be able to handle only few driving situations independently. Therefore, numerous frequently occurring driving situations, such as construction sites, and highway junctions were excluded from the present study.

Fourthly, participants were instructed regarding the driving scenario and the driving maneuver they had to perform prior to each new scenario. This was done to ensure that all participants experienced nearly identical interactions with target vehicles. At the same time, it was also easier for participants to observe the behavioral differences between the target vehicles. However, the proximity to real-world driving was limited due to the instructions and the short interaction time.

Study 2 (see Chapter 7) addresses some of these limitations and open research questions exploring human drivers' reactions to highly automated beyond first contact. To this end, participants experienced repeated interactions with highly automated vehicles during longer highway trips without driving instructions, thereby providing a more "natural" driving setting. In addition, participants were given the chance to observe how highly automated vehicles operate in mixed traffic over a longer period of time. Thus, potential learning effects and behavioral adjustments of human drivers may become more evident than in the present study.

6.6 Conclusions

The present study demonstrated that human drivers can distinguish highly automated vehicles from human-driven vehicles in mixed traffic on the basis of their driving behavior if these vehicles had none or a correct external label. So, human drivers are able to identify the key features of automated driving behavior in first contact, e.g. large safety margins to other vehicles and strict adherence to the maximum permitted speed. Human drivers seem to have an adequate idea of automated driving characteristics and how these vehicles will operate on the highway already. At the same time, the rating scale of perceived driving mode for the four driving behaviors of the target vehicles was never fully exhausted in the examined driving scenarios. Hence, it can be concluded automated driving behavior is still subject to speculation regarding their specific driving behavior and style as human drivers seem to have different expectations regarding highly automated driving behavior.

Following from the obtained results an external labelling of the general capacity to drive automatically is not recommendable. Instead, external labelling should refer to the vehicle's *current* driving mode including a message such as *"highly automated driving mode is active"* or *"manual operation"*. A display of the current driving mode provides an unambiguous information to the question who was currently operating the vehicle – the automated system or the human driver inside. Upon the introduction of a speed limit (S04), human drivers were surprised by automated vehicle's early speed reduction, and by the exact adherence to the speed limit so that safety margins were small at times. In this situation, an external labelling indicating that the vehicle is currently driving in highly automated mode could diminish this surprise effect in the longer run. In more general terms, an external labelling indicating that a vehicle is currently driving in highly automated mode may be particularly useful in situations in which highly automated vehicles behave unusually defensively, resulting in very small safety margins. It is reasonable to assume that an external labelling is more helpful if human drivers additionally received some form of training or education, providing human drivers with some more foundation for building a mental model other than experience.

At the same time, the results of the final survey showed a somewhat ambiguous picture (see Figure 15). Approximately 70 % of the participants in the control group favored the idea of an external labelling, which may be an expression of a certain need for information. In contrast, drivers in the two experimental groups who had experienced some form of external labelling during the simulator drive had a more negative attitude towards labelling.

The present study examined two types of interactions with automated vehicles. In the first type of interaction, automated vehicles reacted to participants' driving behavior. Automated vehicles reacted to human driving behavior by maintaining large safety margins. In the highway access situation (S01), this behavior was acceptable for human drivers. However, the results indicated that human drivers would have preferred more cooperative behavior here, i.e. a lane change, similar to the human configuration of target vehicle behavior. In the lane change situation (S02), automated driving behavior was very defensive and cautious. Human drivers perceived this rule-compliant, defensive driving behavior as pleasant and safe.

In the second type of interaction, human drivers reacted to automated driving behavior. In this type of interaction, automated vehicles' rule-compliance and defensive driving behavior proved rather problematic for human drivers if they had to react to a preceding automated vehicle, e.g. in an overtaking situation (S03) and when a speed limit is introduced (S04). To avoid rear-end collisions at high speeds on the highway, first-generation highly automated vehicles must take into account the cognitive and motor skills of human drivers to react in these driving situations.

7 Study 2 – Repeated contact with highly automated vehicles on the highway

7.1 Objective and research questions

Study 2 extends the scope of Study 1 by exploring the main research question of how human drivers react to highly automated vehicles in repeated interactions during longer highway trips (see Chapter 5.2).

Although it is difficult to predict how the penetration of highly automated vehicles on the highway will develop beyond the introductory phase (Bansal & Kockelman, 2017), most experts agree that there will be a long transition phase where human drivers and highly automated vehicles will share the road in mixed traffic (e.g., Litman, 2021; Zmud et al., 2019; see Figure 2). Thus far, it is completely unclear how human drivers will react to an increasing penetration rate of highly automated vehicles beyond first contact. To the author's knowledge, there are no empirical results available on the effects of different penetration rates of highly automated vehicles on human drivers' experience and driving behavior in mixed traffic on the highway.

Based on the results from previous research (see Fuest et al., 2020; see also Study 1 in the previous chapter), positive and negative effects of mixed traffic on human drivers' experience and driving behavior are conceivable. On the one hand, highly automated driving behavior could serve as role model for human drivers, i.e. human drivers may adapt their driving behavior due to the rule-compliant, defensive driving behavior of highly automated vehicles. This may result in human drivers adhering to speed limits more often and driving more defensively. On the other hand, human drivers may perceive highly automated vehicles as traffic obstacles due to their rule-compliant driving behavior. It may be assumed that the rule-compliant, defensive driving behavior of highly automated vehicles may decelerate subsequent human drivers, compromising their driving goal to arrive at their destination timely (Summala, 2007), which may result in negative emotions, such as driving anger (Mesken et al., 2007; Roidl et al., 2014). Negative emotions including driving anger can, in turn, affect driving performance resulting in maladaptive behavior (Deffenbacher et al., 2002, 2003; Lajunen & Parker, 2001; Mesken et al., 2007; Roidl et al., 2014).

Transferring these findings to the context of mixed traffic, it is reasonable to assume that angry human drivers may display risky and aggressive behaviors toward highly automated vehicles in mixed traffic, e.g., merging closely in front of highly automated vehicles or tailgating automated vehicles, if human drivers perceive highly automated vehicles as impediment to their driving goals. In this context, the external labelling of the highly automated driving mode may encourage risky and aggressive driving behavior as human drivers can instantly identify an automated vehicle (see Connor, 2016; Stanton et al., 2020). In this context, previous research has demonstrated that human drivers (have intentions to) bully automated vehicles on public roads during testing, which has the potential to become a common characteristic of human driver interactions with automated vehicles and lead to safety issues in mixed traffic (Liu et al., 2020).

Based on these considerations, the aim of Study 2 was to explore human driver reactions in terms of experience and driving behavior to highly automated vehicles in mixed traffic depending on the penetration rate of highly automated vehicles and their external labelling on the highway. In contrast to Study 1 in the previous Chapter 6, the focus of the present study was not on individual driving scenarios, but on a longer highway trip in mixed traffic. To this end, human drivers completed four longer highway sections in the driving simulator. Each section had a different penetration rate of highly automated vehicles (within-subjects factor): 0 %, 25 %, 50 % and 75 %. In addition to the penetration rate, the external labelling of automated vehicles was varied (with / without external labelling). As a result of Study 1 (see Chapter 6), an external labelling of the current driving mode proved less confusing to human drivers than a display of a vehicle's general capability to drive automatically. Based on this finding, the external labelling in the present study referred to a vehicle's current driving mode. So, in the experimental group with external labelling, vehicles in highly automated driving mode had an external labelling while human-driven vehicles had no labelling. In the two experimental groups (with / without external labelling), participants knew that they would be driving in mixed traffic. Therefore, a third, uninformed control group was added to the experimental design. Participants in the control group were unaware of the presence of highly automated vehicles and mixed traffic on the highway sections. So, if participants in this control group noticed any behavioral differences between the highly automated and human-driven vehicles based on their driving behavior (alone), the effects in this group would be similar to the effects obtained in the other two experimental groups.

Based on these considerations, the present study explored the following research questions:

RQ 1: Do human drivers from their outside perspective in mixed traffic notice any differences in the penetration rates of highly automated vehicles in mixed traffic on the highway sections?

RQ 2: Does an increasing penetration rate of highly automated vehicles in mixed traffic affect human drivers' perceived safety and comfort during the highway trip?

RQ 3: Does an increasing penetration rate of highly automated vehicles in mixed traffic affect human drivers' emotions during the highway trip?

RQ 4: Do human drivers perceive highly automated vehicles as obstacles or do highly automated vehicles serve as a role model for human drivers in terms of rule-compliant and defensive driving behavior?

RQ 5: Do human drivers adapt their driving behavior due to the increasing penetration rate of highly automated vehicles?

RQ 6: Is an external labelling of vehicles in highly automated driving mode recommendable if the penetration rate of highly automated vehicles in mixed traffic increases?

As it is unclear how human drivers will react to highly automated vehicles in repeated interactions during longer highway trips, no directed hypotheses are presented for these research questions.

7.2 Methods

7.2.1 Experimental design

The present study followed a 3 x 4 mixed design. The within-subjects factor *penetration rate* of highly automated vehicles on the four examined highway sections was varied four-fold: 0 %, 25 %, 50 % and 75 %. The variation of penetration rates referred only to vehicles travelling in the same direction as the ego-vehicle. The opposite lanes were filled with random non-automated traffic to create a more natural driving environment. Each participant completed all four highway sections. To reduce order effects, variations of the factor penetration rate were randomized by means of Latin squares.

Participants were randomly assigned to one of three experimental groups (1) *with external labelling*, (2) *without external labelling*, or (3) the *control group*. In the group with external labelling, the external label referred to the simulated vehicles' *current* highly automated driving mode. As in the previous study (see Chapter 6), vehicles in highly automated driving mode were labelled by means of a blue light rectangle (see Figure 4) whereas the simulated human-driven vehicles had no external labelling in this group. Participants in the group without external labelling were instructed that they will interact with highly automated vehicles on the four highway sections, but that these vehicles could not be distinguished from human-driven vehicles based on their external appearance. Participants in the control group remained unaware of the mixed traffic as participants in this group were instructed that the aim of the present study was to examine how the traffic flow affects drivers' perceived safety and the driving experience in various traffic situations on the highway. No external labelling was used in the control group. Participants in the control group were debriefed about this deception immediately after the final simulator drive. The control group was introduced to examine whether participants noticed any behavioral differences between the simulated highly automated and human-driven vehicles based on their driving behavior alone. Table 19 shows the experimental design as well as the number of participants in each group.

Table 19 Experimental design and number of participants.

	Factor B: Penetration rate (within-subjects)			
Factor A: External labelling (between-subjects)	0 %	25 %	50 %	75%
Correct external labelling	17 participants			
No external labelling	17 participants			
Control group	17 participants			

7.2.2 Driving simulator

As Study 1 (see chapter 6), the present study was carried out in the static driving simulator at the Department of Traffic and Engineering Psychology at Technische Universität Braunschweig (see Chapter 6.2.3).

7.2.3 Highway sections

A German highway with two lanes per direction served as a basis for all four highway sections. Each highway section was 35 000 m long. As participants were instructed to drive as they normally would in real-world driving on the highway, each section took approximately 20 minutes to 25 minutes to complete depending on participants' driving style. The highway sections were identical regarding their construction (infrastructure, route guidance, speed limits). On all highway sections, there was a maximum permitted speed of 130 km/h. In some subsections lower speed limits were introduced by road signs, thus dividing each highway section into ten subsections (see Table 20). To reduce simulator sickness, the ego-vehicle's speed was limited to 150 km/h.

Table 20 Highway sections in Study 2.

<table>
<tr><th colspan="4">Penetration rate of automated vehicles on the highway sections (within-subjects)</th></tr>
<tr><th>0 %
(N = 51 drives)</th><th>25 %
(N = 51 drives)</th><th>50 %
(N = 51 drives)</th><th>75 %
(N = 51 drives)</th></tr>
<tr><td>
<table>
<tr><th>Subsection</th><th>Distance</th><th>Speed limit</th></tr>
<tr><td>1</td><td>0 m – 5000 m</td><td>130 km/h</td></tr>
<tr><td>2</td><td>5000 m – 5500 m</td><td>80 km/h</td></tr>
<tr><td>3</td><td>5500 m – 10000 m</td><td>130 km/h</td></tr>
<tr><td>4</td><td>10000 m – 10500 m</td><td>100 km/h</td></tr>
<tr><td>5</td><td>10500 m – 20000 m</td><td>130 km/h</td></tr>
<tr><td>6</td><td>20000 m – 20500 m</td><td>80 km/h</td></tr>
<tr><td>7</td><td>20500 m – 30000 m</td><td>130 km/h</td></tr>
<tr><td>8</td><td>30000 m – 30500 m</td><td>100 km/h</td></tr>
<tr><td>9</td><td>30500 m – 34500 m</td><td>130 km/h</td></tr>
<tr><td>10</td><td>34500 m – 35000 m</td><td>80 km/h</td></tr>
</table>
</td><td>Same as “0 %”</td><td>Same as “0 %”</td><td>Same as “0 %”</td></tr>
</table>

The experts’ statements (see Chapter 6.2.1) and the driving scenarios from Study 1 served as a basis for the design of the highway sections. So, the highway sections in the present study included only driving situations which highly automated vehicles will presumably be able to master independently, e.g., overtaking slower vehicles and trucks, car-following, and adapting speed to speed limits (see Study 1, S01 to S04 in Table 1). Hence, there were no construction sites, highway junctions, missing lane markings, extreme weather conditions or similar circumstances that may require human intervention as stated by the experts.

7.2.4 Automated and human-driven target vehicle behavior on the highway sections

As in Study 1, highly automated and human driving behavior in the present study was modelled based on the expert interviews (see Chapter 6.2.1). To this end, a modified version of the behavioral model *EXWDM* was applied to all simulated vehicles (WIVW, 2017). This behavioral model is based on Wiedemann’s (1974, as cited in WIVW, 2017) vehicle following model and the lane change model MOBIL (WIVW, 2017). In car-following, all simulated vehicles aimed to maintain a pre-defined speed level, taking into account pre-defined safety margins to preceding vehicles (WIVW, 2017). The lane change model MOBIL allows simulated vehicles to change lanes independently depending on pre-defined parameters (WIVW, 2017). A detailed description of the model can be found in WIVW (2017).

On subsections with a speed limit of 130 km/h, the pre-defined target speed of highly automated vehicles was set to 100 km/h and 110 km/h respectively. On subsections with lower speed limits of 100 km/h and 80 km/h, respectively, the target speed was set to the maximum permitted speed. Once a speed limit was removed, highly automated vehicles accelerated only *after* passing the corresponding sign. In contrast, human-driven vehicles failed to adhere to the maximum permitted speed. The pre-defined target speed of simulated human-driven vehicles was 130 km/h on all subsections regardless of the specific speed limits. Upon the introduction of speed limits, some simulated human-driven vehicles exceeded the maximum permitted speed or started to brake at the corresponding sign. Regarding the pre-defined target speeds in the behavior model, it should also be noted that these varied depending on the behavior of the participant in the ego-vehicle. In addition, the speed of simulated vehicles was determined by the pre-defined safety margin to the preceding vehicles, being at least 2.75 s time headway for highly automated vehicles and at least 1.2 s time headway for human drivers. Furthermore, highly automated and human-driven vehicles differed in terms of lane center guidance within their own lane. While highly automated vehicles drove in the center of the lane without lateral deviations, human-driven vehicles showed lateral deviations of up to one meter to the right and left from the center of the lane resembling human driving behavior.

The simulated automated and human-driven vehicles were placed in front and behind the ego-vehicle during the course of each highway section to create a natural traffic flow. In addition, there were eight trucks (80 km/h) on each highway section to prompt participants in the ego-vehicle to change lanes.

In contrast to Study 1, participants were given no instructions regarding their driving behavior and style including speed choice, safety margins to surrounding vehicles and lane changes in the present study. Instead, participants were instructed to drive as they would in their own vehicle in real-world driving. Thus, participants in the ego-vehicle were encouraged to show their “natural” driving behavior in the interactions with the simulated vehicles. As a consequence, the number of interactions with surrounding vehicles largely depended on participants’ driving behavior and driving style.

7.2.5 Dependent variables

To measure human driver reactions to highly automated driving behavior on the highway sections, both questionnaire data and driving data were collected in the present study.

7.2.5.1 Questionnaire data

After each highway section, participants rated comfort and perceived efficiency on a 5-point Likert scale as well as perceived safety on an 8-point scale (adapted from Neukum et al., 2008; see Figure 6). Furthermore, participants were asked to estimate the penetration rate of highly automated vehicles on the previous highway section. In addition, participants in the informed experimental groups with and without external labelling were asked whether they had perceived any behavioral differences between highly automated and human-driven vehicles. Table 21 provides a summary of all measured questionnaire data.

Table 21 Questionnaire data measured in Study 2.

Outcome variable	Description
Perceived safety	Item [1 (“harmless”) … 8 (“not acceptable”)] “What category describes your perception of the traffic situation on the previous highway section best?”
Comfort	Item [1 (“very unpleasant”) … 5 (“very pleasant”)] “How pleasant was the drive on the previous highway section?”
Perceived efficiency	Item [1 (“very inefficient”) … 5 (“very efficient”)] “How well did you progress on the previous highway section?”
Perceived penetration rate*	Item [0 % … 100 %] “What percentage of the other vehicles that drove with you on the highway were, in your estimation, were automated vehicles on a scale of 0 % to 100%? This question only applies to vehicles that were travelling in the same direction as you.”
Difference between highly automated and human driving behavior*	Item [yes; no] “Did you think that the automated vehicles behaved differently from human drivers?”

***Note.* *These outcome variables were not measured in the control group.**

Furthermore, participants rated the emotions they had experienced while driving on an internally revised version of the Geneva Emotion Wheel (see Huemer et al., 2019; adapted from Scherer et al., 2005 and Frehse, 2015; www.unige.ch/cisa/gew) after each highway section (see Figure 16). Participants rated only emotions matching their experience on the previous highway section on a scale from 1 (*very weak*) to 5 (*very strong*). If participants had experienced no emotion during the previous simulator drive, they checked the inner circle *no emotion felt*.

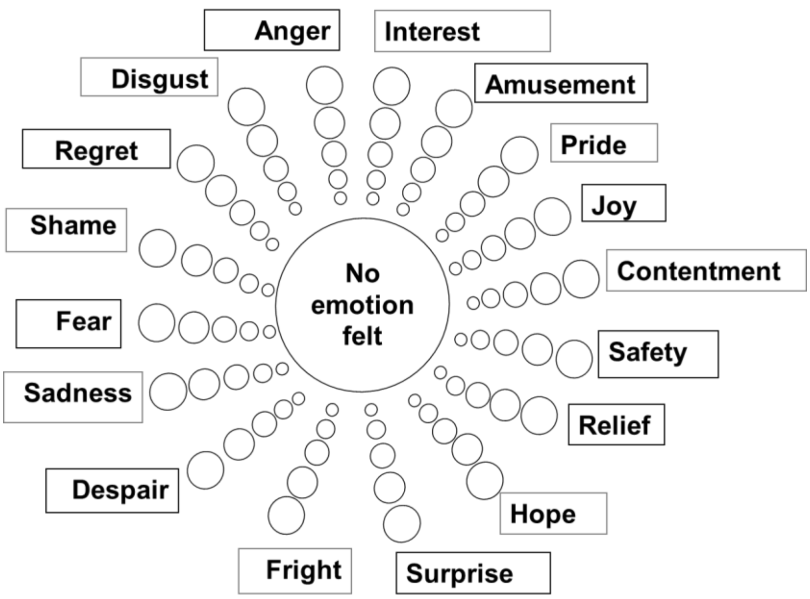


Figure 16 Revised version of the Geneva Emotion Wheel applied in Study 2.

7.2.5.2 Driving data

Regarding the adaptation of driving behavior to mixed traffic, two aspects of participants' driving behavior were analyzed, (1) safety margins (as measured by time headway) to preceding vehicles and (2) speed adaptation. To this end, the positions of all vehicles were recorded throughout the entire simulator drive. Based on these positions, participants' mean and minimum time headways to preceding vehicles in car-following situations were calculated as indicators of safety-criticality in mixed traffic interactions. In the analysis of safety-criticality, only interactions in which a preceding vehicle was present (< 3 s time headway between the ego-vehicle and preceding vehicle). In addition, extremely short time headways (< 0.1 s) were excluded as these were caused by errors in driving data recording. On this basis, the percentage of safety-critical (< 1.0 s) time headways to preceding vehicles was calculated for each subsection. Subsequently, the results were summarized for each of the three speed zones (80 km/h, 100 km/h, 130 km/h).

An increasing penetration rate of highly automated vehicles in mixed traffic may change human drivers' behavior as an adaptation to adhere more closely to the maximum permitted speeds due to the compliance of highly automated vehicles. The analysis of the speed profiles of ego-vehicles can provide initial indications as to whether participants complied with the traffic rules. To this end, the average speed was calculated for each participant, analogous to the safety-criticality indicators for all ten subsections of a simulator drive. These results were then summarized for each of the three speed ranges (80 km/h, 100 km/h, 130 km/h). The driving data measured in the present study are summarized in Table 22.

Table 22 Driving data in the present study.

Measurement	Unit	Description
Safety-criticality of interactions		
Mean time headway to preceding vehicles	s	Mean time headway to preceding vehicles (between 0.1 s and 3.0 s time headway) in the three speed zones (80 km/h, 100 km/h, 130 km/h)
Minimum time headway to preceding vehicles	s	Minimum time headway to preceding vehicles (between 0.1 s and 3.0 s time headway) in the three speed zones (80 km/h, 100 km/h, 130 km/h) s
Percentage of safety-critical interactions with preceding vehicles	%	Percentage of interactions with preceding vehicles that included close following (< 1.0 s time headway) in the three speed zones (80 km/h, 100 km/h, 130 km/h)
Speed adaptation		
Average speed	km/h	Participants' average speed in the three speed zones (80 km/h, 100 km/h, 130 km/h)

Furthermore, the number of highly automated and human-driven vehicles were recorded for each highway section.

7.2.6 Procedure

Upon arrival, participants were acquainted with the experimental procedure and signed informed consent for the scientific use of their data. Participants were informed that they were free the drop out of the study at any point without any disadvantages. Participants then completed the socio-demographic questionnaire, which included questions on mobility behavior, experience with driver assistance systems, technical affinity and the state of knowledge as well as attitudes towards the topic of highly automated driving.

Next, each participant was randomly assigned to one of the three experimental groups. As the present study aimed to examine human driver reactions to highly automated vehicles beyond first contact, participants in the two experimental groups with and without external labelling received detailed information on highly automated vehicles' driving capabilities and system limits according to SAE Level 3 (SAE, 2014, 2018). This information phase enabled participants to acquire some knowledge of highly automated driving behavior in typical highway driving situations prior to the simulator drives. Participants watched three videos on a tablet, showing video footage was pre-recorded from the driving scenarios used in Study 1 including overtaking (S03), maintaining a minimum time headway in a car-following situation (S02) and braking in when advancing a speed limit sign (S04). The information phase also served to acquaint participants in the group *with external labelling* with the labelling's function to display an automated vehicle's *current* driving mode. So, participants knew for sure that simulated vehicles with a blue rectangle were in highly automated driving mode whereas simulated vehicles without a blue rectangle were human-driven vehicles. Participants in the group *without external labelling* received the information that highly automated vehicles and human-driven vehicles could not be distinguished based on their external appearance. In these two groups, the information phase was followed by the training drive.

In contrast, participants in the control group remained unaware of the presence of highly automated vehicles on the highway sections. Instead, participants in this group were told that the objective of the present study was to examine the influence of traffic flow on drivers' safety perception on the highway. In the control group, the training drive immediately followed the completion of the sociodemographic questionnaire without an information phase in between.

By means of a 5-minute training drive, all participants were given the chance to acquaint themselves with the experimental situation and driving in the driving simulator. The training drive was not included in data analysis. After the training drive, all participants were instructed that they should drive on the following four highway sections as if they were driving in their own car in real-world driving. This was done to ensure that participants showed their "natural" driving behavior. To avoid order effects, the highway sections were presented in a random order.

After each highway section, participants reached a highway parking lot where participants completed a questionnaire on the previous drive. In addition to questionnaire data, driving data including participants' speed and position, as well as time headways to target vehicles were recorded for each highway section. Each of the four highway section took approximately 20 minutes to 25 minutes to complete depending on participants' driving style. In total, the simulator drive took approximately 80 to 100 minutes per participant. The entire simulator drive was recorded by means of a video camera (GoPRO Hero 3+) placed on the simulator dashboard, adjusted with wide-angle to film the entire scenery from the participant's perspective in the ego-vehicle. This was done to facilitate the detection of errors in the driving data recording and the manipulation of the simulated vehicles' driving behavior.

7.2.7 Participants

Fifty-four participants took part in the present study. Participants were recruited from an internal database. Three participants dropped out of the study due to motion sickness. The final sample consisted of N = 51 participants aged 22 to 74 years (M = 41.5 years, SD = 18.1 years, 22 female). On average, the participants had their driving license for 24 years (SD = 19.0 years). 31 (61 %) participants stated that they drove at least several times a week. Another 10 (20 %) participants drove at least several times a month. 45 % of the participants reported driving more than 9000 km per year. 78 % of the participants had experience with driver assistance systems. Participants' technical affinity was average with a mean value of M = 3.88 (SD = 0.96) on the 6-point ATI scale (Affinity for Technology Scale; Franke et al., 2019). More than two thirds of the participants (71 %) had already gained experience in the driving simulator at least once. Participants' attitude towards automated driving was predominantly positive with 45 % of the participants stated that they had a rather positive or a very positive attitude towards automated driving whereas 14 % of the participants had a negative or a very negative attitude. 41 % of the participants were undecided.

A prerequisite for participation in the driving simulator study was a valid driving license. All participants had normal or corrected-to-normal vision. Data collection took place from January to February 2020 at the Department of Traffic and Engineering Psychology at Technische Universität Braunschweig. The experiment lasted approximately 120 minutes to 150 minutes per participant. Participation was reimbursed with 20 to 25 EURO depending on the duration of the experiment. Undergraduate Psychology students at Technische Universität Braunschweig could choose between monetary reimbursement or course credit. The study was approved by the ethics committee of the Faculty of Life Sciences at Technische Universität Braunschweig.

7.2.8 Data analysis

7.2.8.1 Manipulation check

As a manipulation check of the within-subjects factor *penetration rate*, the number of highly automated and human-driven vehicles was recorded for each of the four highway sections to examine whether the actual penetration rate of highly automated vehicles in the driving simulator study matched with the penetration rate on each highway section in the experimental design (see Table 19). If the manipulation was successful, there would be none or only minor deviations from the experimental design.

7.2.8.2 Questionnaire data

At first, the outcome variables *perceived safety*, *comfort*, and *efficiency* were each analyzed by means of a 3 x 4 mixed ANOVA (with post-hoc pairwise comparisons) including the within-subjects factor *penetration rate* the between-subjects factor *external labelling*. Overall, questionnaire data from 204 simulator drives (4 highway sections x 51 participants) were recorded. There was no missing data in the analysis. The analysis of the outcome variable *perceived safety* revealed that n = 12 ($n_{\text{with labelling}}$ = 5, $n_{\text{without labelling}}$ = 4, $n_{\text{control group}}$ = 3) drivers rated driving in non-automated traffic without automated vehicles as *dangerous* or *situation not acceptable* on the 8-point safety scale. Further analyses provided no evidence that sample characteristics had affected the perceived safety ratings. These participants had no less (simulator) driving experience, or technical affinity than the rest of the sample. In addition, the analysis of the video data provided no indication of any special, safety-critical situations during the simulator drives in this group of participants. Thus, it can be assumed that these participants either misunderstood the safety scale or they used an incorrect reference system. Therefore, the data sets of these participants were excluded from further analysis of the described outcome variables. So, the final analysis of the questionnaire data included data from 156 simulator drives (4 highway sections x 39 participants). This corresponds to 76.5 % of all questionnaire data.

Subsequently, the outcome variable *perceived penetration rate* was analyzed by means of a 2 x 4 mixed ANOVA with pairwise comparisons for the within-subjects factor penetration rate and the between-subjects factor external labelling. This outcome variable was not measured in the control group as participants in this group were unaware of the mixed traffic. So, the between-subjects factor external labelling was reduced to the two experimental groups with and without external labelling. In the group with external labelling, perceived penetration rate was further not measured in the condition with 0 % penetration rate as participants in this group knew for sure that there were no highly automated vehicles present on this highway section. Overall, questionnaire data from 119 simulator drives completed by *n* = 34 participants ($n_{\text{with labelling}}$ = 17, $w_{\text{ithout labelling}}$ = 17) were recorded. However, data from *n* = 9 participants were excluded from questionnaire data analysis due to their perceived safety ratings. So, questionnaire data from 88 simulator drives completed by *n* = 25 participants ($n_{\text{correct labelling}}$= 12 participants, $n_{\text{no labelling}}$ = 13 participants). This corresponds to 73.5 % of all questionnaire data.

Finally, participants' emotion ratings on the Geneva Emotion Wheel were analyzed for 156 simulator drives (4 x 39 participants). To categorize participants' self-reported emotions, a principal component analysis was conducted on the 17 items with Varimax rotation. Based on the eigenvalues (Kaiser-criterion), three factors were retained. The first factor represented negative emotions, the second factor represented positive emotions, and the third factor represented predominantly surprise and anger. Based on this three-factor solution, three emotion scales were constructed by calculating the mean score on each scale for each participant. The first two scales factors had high reliabilities (α = .90, α = .79) whereas the third scale had a low reliability (α = .61). Therefore, this scale was excluded from further analysis. As anger was named the most frequently occurring emotion being elicited in over half of all simulator drives, anger was analyzed separately by means of a mixed ANOVA including the within-subjects factor penetration rate and the between-subjects factor external labelling. The two remaining emotion scales were analyzed in the same way.

All reported means in the present study including both questionnaire and driving data (see Chapter 7.2.8.3.) are presented with 95 % confidence intervals (CI). If the assumption of sphericity was violated in the ANOVAs, degrees of freedom were corrected using either a Greenhouse-Geisser correction (ε < .75), or a Huynh-Feldt-correction (ε > .75). For significant results of the ANOVAs, η^2p is reported as an effect size. A significance level of $p \leq .05$ was adopted in all statistical tests. In regard of the exploratory approach of the study, alpha was not adjusted in order to better detect relevant effects while at the same time minimizing interpreting random variations. For results of all pairwise comparisons for the main effects of the factors *penetration rate* and *external labelling* refer to Tables C1 and C2 in Appendix C. For statistical data analysis IBM SPSS statistics 25 was applied.

7.2.8.3 Driving data

Driving data from 204 simulator drives were recorded (4 highway sections x 51 participants). The data sets of *n* = 2 participants were missing due to technical issues during data recording. In total, driving data from 196 simulator drives from *n* = 49 participants were analyzed which corresponds to 96 % of all driving data. Furthermore, the last subsection with a speed limit of 80 km/h (34500 m – 35000 m) was excluded from driving data analysis because participants had already braked in this section to reach the parking lot. The results for each outcome variable were calculated and analyzed for the three speed zones (80 km/h, 100 km/h, 130 km/h).

All outcome variables were each analyzed by means of 3 x 4 mixed ANOVAs (with post-hoc pairwise comparisons) including the within-subjects factor *penetration rate* and the between-subjects factor *external labelling.* ANOVAs were carried out separately for the three speed zones (80 km/h, 100 km/h, 130 km/h). For results of all pairwise comparisons for the main effects of the factors *penetration rate* and *external labelling* refer to Tables C3 and C4 in Appendix C.

As safety-criticality measures were analyzed only if a preceding vehicle was present in the range from 0.1 s to 3 s time headway ahead of the ego-vehicle (see Chapter 7.2.5.2). Minimum and average time headways were only calculated for n = 27 participants in the 100 km/h speed zone, and for n = 30 participants in the 80 km/h speed zone. All other participants kept larger safety margins (> 3 s time headway) to preceding vehicles in these speed zones. In the 130 km/h speed zone, data from all participants were included (n = 49 participants).

7.3 Results

7.3.1 Manipulation check

To check whether the penetration rate of highly automated vehicles in the simulator study matched the experimental design, the number of highly automated and human-driven vehicles was recorded for each of the four highway sections (0 %, 25 %, 50 %, 75 %). As can be seen in Figure 17, the actual penetration rate of highly automated vehicles on the highway sections corresponded to the experimental design on average except for minor deviations. In the condition with 25 % highly automated vehicles, 23.4 % of the simulated vehicles were highly automated. In the conditions with 50 % and 75 % highly automated vehicles, the deviations from experimental design were somewhat greater. In the 50 % condition the actual penetration rate was 44.1 %, and in the 75 % condition an average of 61.0 % of the vehicles were highly automated. Overall, the manipulation of the within-subjects factor penetration rate was successful.

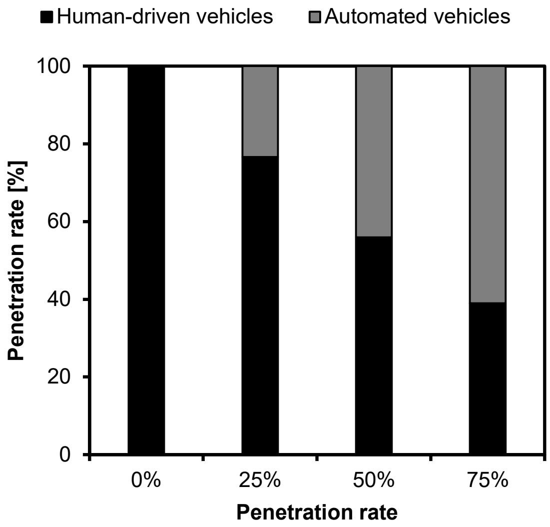


Figure 17 Penetration rate (%) of highly automated vehicles and human-driven vehicles on the highway sections.

7.3.2 Questionnaire data

7.3.2.1 Subjective ratings

The statistical tests performed for the outcome variables perceived safety, comfort, perceived efficiency and perceived penetration rate are reported in Table 23. Table 24 provides the mean values and standard deviations for these outcome variables. The two-way mixed ANOVAs revealed four significant main effects of the within-subjects factors penetration rate on perceived safety (see Figure 18 left), comfort (see Figure 18 right), efficiency (see Figure 19) and perceived penetration rate as well as a significant two-way interaction effect of the within-subjects factor penetration rate and the between-subjects factor external labelling on perceived penetration rate (see Figure 20). No further significant interaction effects or main effects were found in the analyses.

Table 23 Statistical tests (mixed ANOVA) for differences between experimental groups, and the penetration rates of highly automated vehicles regarding the outcome variables perceived safety, comfort, perceived efficiency and perceived penetration rate.

	Effect	F	df	p	η^2_p
Perceived safety*	P (Penetration rate)	3.6	2.3,83.1	**.026**	.09
	E (External labelling)	0.6	2,36	.585	
	P x E	0.4	4.6,83.1	.812	
Comfort*	P	2.9	2.7,96.9	**.047**	.07
	E	0.1	2,36	.948	
	P x E	1.2	5.4,96.9	**.333**	
Perceived efficiency*	P	4.1	2.5,91.6	**.012**	.10
	E	0.5	2,36	.603	
	P x E	0.8	5.1,91.6	.544	
Perceived penetration rate**	P	14.7	2.8,64.0	**< .001**	.39
	E	0.9	1,36	.362	
	P x E	15.4	2.8,64.0	**< .001**	.40

***Note.* Significant p-values in bold. *N = 39. ** N = 25.**

Table 24 Mean values and standard deviations including experimental groups, and the penetration rates of highly automated vehicles regarding the outcome variables perceived safety, comfort, perceived efficiency and perceived penetration rate.

		Penetration rate			
	External labelling	0 %	25 %	50 %	75 %
Perceived safety	With labelling	2.08 (0.90)	2.75 (1.91)	2.25 (1.66)	2.75 (1.60)
	Without labelling	1.77 (0.60)	3.31 (2.14)	3.00 (1.92)	3.15 (2.15)
	Control group	2.21 (0.89)	3.14 (1.83)	2.29 (0.83)	2.86 (1.46)
Comfort	With labelling	4.00 (0.95)	3.58 (1.17)	3.92 (1.08)	3.17 (1.03)
	Without labelling	4.08 (0.86)	3.54 (0.66)	3.38 (1.26)	3.77 (1.17)
	Control group	4.07 (0.83)	3.93 (1.00)	3.43 (0.94)	3.57 (1.22)
Perceived efficiency	With labelling	4.25 (0.45)	3.92 (1.00)	4.08 (0.52)	3.58 (1.17)
	Without labelling	4.15 (0.69)	3.54 (0.97)	3.62 (0.87)	3.69 (0.95)
	Control group	4.29 (0.61)	4.14 (0.86)	3.71 (0.99)	3.43 (1.28)
Perceived penetration rate*	With labelling	*	16.67 (14.79)	29.67 (21.02)	60.42 (19.12)
	Without labelling	39.92 (27.42)	26.15 (19.38)	28.46 (23.66)	35.92 (30.18)
	Control group	*	*	*	*

***Note.* *Perceived penetration rate was not measured in these conditions.**

As can be seen in Figure 18 left, the subject ratings of perceived safety were lowest (= safest) in the condition with 0 % automation, being rated *a little unpleasant* (M = 2.02). This condition was followed by the mixed traffic conditions with 50 % automation (M = 2.51), and 75 % penetration rate (M = 2.92). The condition with 25 % automation was rated as the most unpleasant (M = 3.07). Pairwise comparisons revealed significant differences between the condition with 0 % automation and 25 % and 75 % condition, with a trend for the 50 % condition (p = .077; see Appendix C). Perceived safety ratings changed by approximately one scale point over the four conditions, with all mean ratings being located in the lower half of the scale and ranging between the labels *a little unpleasant* and *medium unpleasant.*

Comfort ratings (see Figure 18 right) were highest in the condition with 0 % automation (M = 4.05), being rated *rather pleasant*, followed by the conditions with 25 % and 50 % highly automated vehicles (M = 3.68, M = 3.58). The condition with 75 % automation was rated the least pleasant (M = 3.50). So, drivers rated driving in non-automated traffic significantly more pleasant than driving in mixed traffic regardless of the exact penetration rate of highly automated vehicles. Pairwise comparisons revealed significant differences between the condition with non-automated traffic and all three conditions with mixed traffic (see Appendix C). Overall, comfort ratings ranged between the labels *rather pleasant* and *medium pleasant*, with all mean ratings being located in the upper half of the scale.

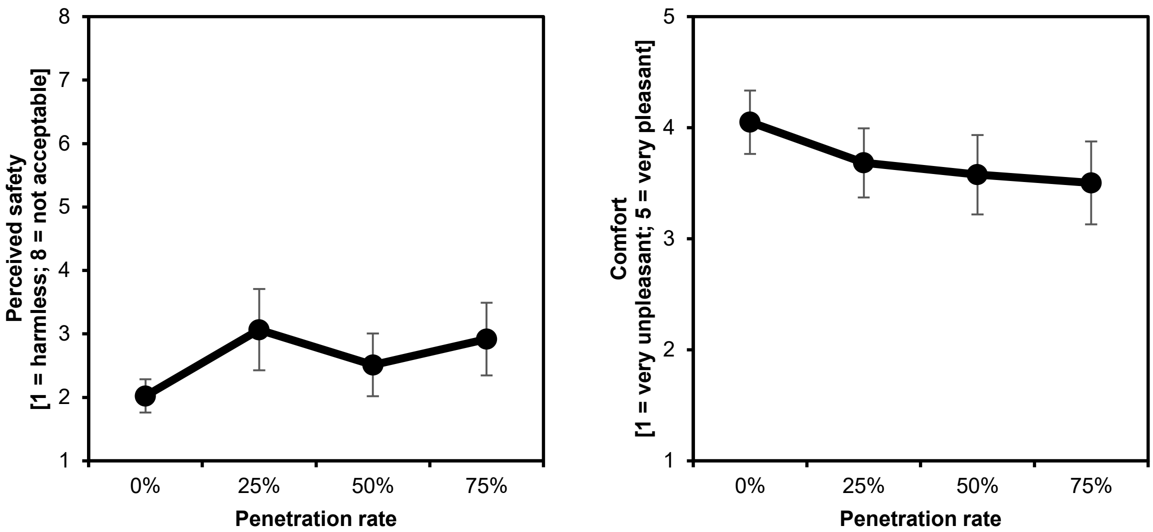


Figure 18 Left: Perceived safety rating (means with 95 % CI) depending on penetration rate (P) and external labelling (E). Right: Comfort rating (means with 95 % CI) depending on penetration rate (P) and external labelling (E).

Similar patterns emerged regarding the subjective ratings of perceived efficiency. As Figure 19 shows, perceived efficiency ratings were highest in the condition with 0 % automation, being rated *rather efficient* (M = 4.23). It was followed by the condition with 25 % automation (M = 3.87), and 50 % automation (M = 3.80). The condition with 75 % highly automated vehicles was rated the least efficient (M = 3.57). Pairwise comparisons showed significant differences between the condition with non-automated traffic and the other three conditions with mixed traffic (see Appendix C). Overall, perceived efficiency ratings ranged in the upper half of the rating scale.

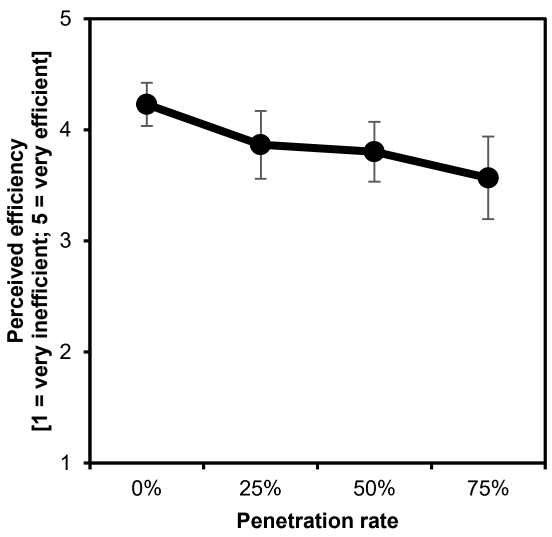


Figure 19 Perceived efficiency rating (means with 95 % CI) depending on penetration rate (P) and external labelling (E).

Figure 20 shows the interaction effect of the within-subjects factor penetration rate and the between-subjects factor external labelling on the estimated penetration rate of highly automated vehicles on the highway sections. As can be seen, human drivers estimated the penetration rate of highly automated vehicles more correctly if the simulated vehicles' current driving mode was externally labelled compared to no external labelling. In the group with external labelling, the estimate increased in line with the actual penetration rate. Despite the correct tendency of the estimations, participants in the group with external labelling underestimated the penetration rate in the conditions with 25 % and 50 % automation ($M_{25\,\%}$ = 16.7 %, $M_{50\,\%}$ = 29.7 %). Regarding the condition with 75 % automation, the manipulation check revealed an actual penetration rate of 60.4 % highly automated vehicles in this condition (see Figure 17). So, participants estimated the percentage of highly automated vehicles in this condition correctly ($M_{75\,\%}$ = 60.9 %).

In the group without external labelling, however, participants' estimations ranged between 26 % and 38 % across conditions ($M_{0\,\%}$ = 39.6 %, $M_{25\,\%}$ = 26.2 %, $M_{50\,\%}$ = 28.5 %, $M_{75\,\%}$ = 35.9 %). These estimations were inaccurate except for the condition with 25 % highly automated vehicles, which may be a random finding. No systematic pattern of estimations was identified in this experimental group.

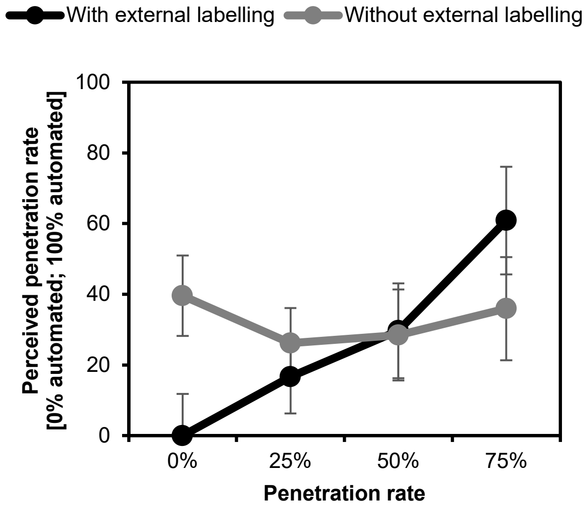


Figure 20 Perceived penetration rate rating (means with 95 % CI) depending on penetration rate (P) and external labelling (E).

7.3.2.2 Emotion ratings on the Geneva Emotion Wheel

Table 25 summarizes the descriptive statistics (count, mean, standard deviation) of the emotion ratings on the Geneva emotion wheel. As expected based on previous literature (Roidl et al., 2014), anger was the most frequent emotion, being present in over half (58 %) of all simulator drives. The least frequent emotion was sadness, being chosen in only 8 % of all simulator drives. Regarding intensity, mean ratings of most emotions were in the lower end of the 5-point scale. The intensity of anger, however, was in the lower mid-range of the scale (*M* = 2.20).

Table 25 Count, means, and standard deviations for all emotions on the Geneva Emotion Wheel.

Item	Count	Mean (SD)	Minimum	Maximum
Anger	90	2.20 (2.08)	0	5
Surprise	79	1.79 (1.94)	0	5
Contentment	78	1.68 (1.85)	0	5
Fright	68	1.59 (1.99)	0	5
Interest	60	1.35 (1.81)	0	5
Safety	57	1.15 (1.65)	0	5
Fear	43	0.63 (1.63)	0	5
Joy	43	0.90 (1.57)	0	5
Pride	38	0.92 (1.72)	0	5
Relief	35	0.84 (1.68)	0	5
Contempt	30	0.81 (1.73)	0	5
Despair	28	0.76 (1.70)	0	5
Regret	30	0.81 (1.73)	0	5
Amusement	28	0.70 (1.58)	0	5
Shame	21	0.63 (1.63)	0	5
Hope	20	0.46 (1.27)	0	5
Sadness	12	0.38 (1.32)	0	5

A principal component analysis was conducted on the 17 items of the Geneva Emotion Wheel wit Varimax rotation. The Kaiser-Meyer-Olkin measure verified the sampling adequacy for this analysis (KMO = .884). As can be seen in Table 26, the principle component analysis converged after eleven iterations and produced three factors, each explaining a variance of more than 1 item (Kaiser-criterion). The overall model explained 58 % of the total variance (17 items).

Table 26 Rotated factor loadings on the principle components.

	Component		
Item	1	2	3
Hope	**.636**	.534	
Regret	**.746**		.314
Sadness	**.814**	.409	
Fear	**.683**		.366
Shame	**.790**		
Despair	**.702**		
Contempt	**.619**		.404
Safety		**.721**	
Relief	.368	**.554**	
Contentment		**.645**	
Joy	.303	**.576**	
Pride	.394	**.558**	
Interest		**.597**	
Amusement	.407	**.550**	
Surprise		.358	**.727**
Fright	.441		**.713**
Anger			**.577**
Eigenvalue	4.42	3.35	2.03
% of explained variance	26.04	19.71	11.92
α	.90	.79	.61

Note. **The rotation converged in 11 iterations. Highest factor loadings for each item in bold.**

Based on the results of the analysis, 17 emotions were summarized into three emotion scales. Due to the low reliability of the third scale (α = .61), this scale was eliminated from further analysis. The statistical tests performed for the two emotion rating scales and anger are reported in Table 27. Table 28 provides the mean values and standard deviations for the two emotion scales and anger. The analyses revealed neither significant main effects, nor significant interaction effects of the factors external labelling, and penetration rate on the emotion ratings.

Table 27 Statistical tests (mixed ANOVA) for differences between experimental groups and the penetration rate of highly automated vehicles regarding the two emotion scales and anger.

	Effect	*F*	*df*	*p*
Negative emotion	P (Penetration rate)	1.6	2.9,104.4	.185
	E (External labelling)	0.7	2,36	.510
	P x E	0,5	5.8,104.4	.780
Positive emotion	P	0.2	3,108	.924
	E	1.9	2,36	.171
	P x E	1.8	6,108	.105
Anger	P	0.8	3,108	.522
	E	0.8	2,36	.464
	P x E	0.4	6,108	.905

Table 28 Means and standard deviations for the two emotion scales and anger.

		Penetration rate			
	External labelling	0 %	25 %	50 %	75 %
Negative Scale	With labelling	0.39 (0.52)	0.26 (0.37)	0.36 (0.52)	0.44 (0.60)
	Without labelling	0.66 (1.19)	0.79 (1.26)	0.71 (1.35)	0.95 (1.34)
	Control group	0.90 (1.72)	0.98 (1.83)	0.85 (1.68)	1.01 (1.68)
Positive Scale	With labelling	0.63 (0.58)	0.49 (0.61)	0.60 (0.55)	0.71 (0.47)
	Without labelling	1.27 (0.90)	1.37 (1.14)	1.10 (1.08)	0.96 (0.91)
	Control group	1.38 (1.38)	1.28 (1.45)	1.47 (1.60)	1.43 (1.54)
Anger	With labelling	2.17 (2.13)	1.83 (1.99)	1.92 (2.02)	2.58 (1.56)
	Without labelling	1.38 (1.94)	2.46 (2.18)	1.77 (2.35)	2.00 (2.00)
	Control group	2.14 (2.28)	2.79 (2.33)	2.43 (2.24)	2.79 (2.08)

7.3.3 Driving data

7.3.3.1 Average speed

The statistical tests performed for the outcome variable average speed are reported in Table 29. Table 30 provides the mean values and standard deviations for average speed. The two-way mixed ANOVAs revealed significant main effects of the within-subjects factor penetration rate on average speed in all three speed zones (130 km/h, 100 km/h, 80 km/h; see Figure 21 – Figure 23). No further significant main effects or interaction effects were found in the analysis.

Table 29 Statistical tests (mixed ANOVA) for differences between experimental groups and the penetration rate regarding the outcome variable average speed (130 km/h, 100 km/h, 80 km/h).

	Effect	*F*	*df*	*p*	η^2_p
130 km/h	P (Penetration rate)	4.8	1.7,77.3	**.015**	.10
	E (External labelling)	0.3	2,46	.754	
	P x E	0.6	3.4,77.3	.654	
100 km/h	P	4.2	2.3,105.8	**.014**	.08
	E	1.0	2,46	.369	
	P x E	1.6	4.6,105.8	.161	
80 km/h	P	7.7	3,138	**< .001**	.14
	E	1.1	2,46	.351	
	P x E	0.5	6,138	.806	

***Note.* Significant p-values in bold.**

Table 30 Mean values and standard deviations including experimental groups and the penetration rate regarding the outcome variable average speed (130 km/h, 100 km/h, 80 km/h).

		Penetration rate			
	External labelling	0 %	25 %	50 %	75 %
130 km/h	With labelling	125.81 (6.27)	124.36 (8.83)	124.76 (7.90)	123.95 (7.86)
	Without labelling	125.12 (3.81)	122.64 (5.61)	123.13 (6.91)	120.26 (9.19)
	Control group	126.19 (9.79)	124.24 (10.95)	123.44 (8.36)	119.76 (14.18)
100 km/h	With labelling	107.15 (6.15)	104.41 (9.86)	104.46 (6.71)	106.19 (8.92)
	Without labelling	104.52 (5.70)	102.52 (5.76)	100.58 (6.18)	101.13 (6.09)
	Control group	108.16 (8.88)	105.20 (8.51)	105.48 (10.74)	99.99 (14.50)
80 km/h	With labelling	91.14 (11.31)	88.92 (12.27)	89.61 (9.62)	86.51 (7.08)
	Without labelling	87.19 (4.58)	85.93 (4.57)	85.91 (8.02)	81.26 (8.94)
	Control group	91.75 (8.83)	90.33 (12.19)	87.10 (11.14)	85.36 (13.43)

In the 130 km/h speed zone (see Figure 21), the average speed was highest in the 0 % condition without non-automated traffic (M = 125.7 km/h). It was followed by the conditions with 25 % and 50 % automation (M = 123.7 km/h, M = 123.8 km/h). The average speed was lowest in the condition with 75 % automation (M = 121.3 km/h). Participants' average speed decreased by approximately 4 km/h over the four conditions. Pairwise comparisons revealed that participants' average speed was significantly higher in non-automated traffic (0 % condition) compared to other three conditions with mixed traffic (25 %, 50 %, 75 % automation). In addition, there was a significant difference between the 50 % and 75 % conditions (see Appendix C). Regarding rule-compliance, drivers' average speed was lower than the maximum permitted speed on all four highway sections.

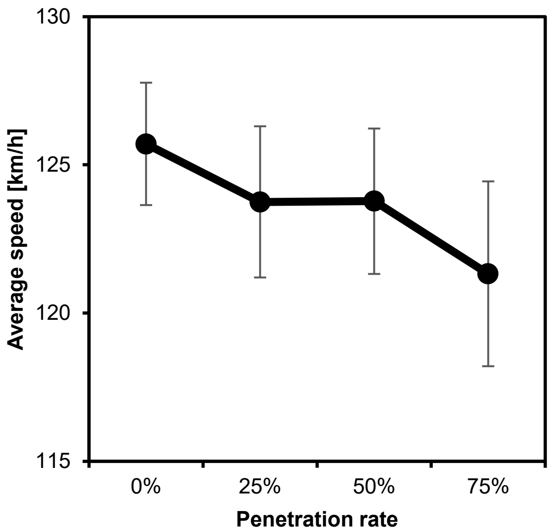


Figure 21 Average speed (means with 95 % CI) depending on penetration rate (P) and external labelling (E) on highway sections with a speed limit of 130 km/h.

Similar patterns emerged in the 100 km/h zone (see Figure 22). Participants' average speed was highest in non-automated traffic (M = 106.6 km/h), followed by the conditions with 25 % and 50 % highly automated vehicles (M = 104.0 km/h, M = 103.5 km/h). The average speed was lowest in the condition with 75 % highly automated vehicles (M = 102.4 km/h). Although participants' average speed had decreased by approximately 4 km/h to M = 102.4 km/h in the condition with 75 % highly automated vehicles compared to non-automated traffic, drivers still exceeded the maximum permitted speed of 100 km/h in this condition. Pairwise comparisons revealed that average speed was significantly higher in non-automated traffic compared to the other three mixed traffic conditions (see Appendix C).

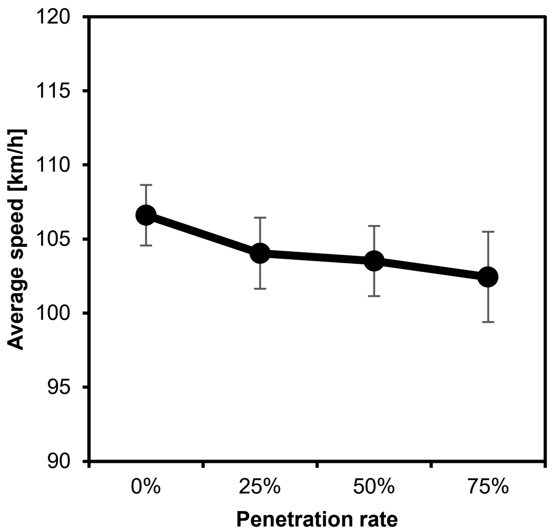


Figure 22 Average speed (means with 95 % CI) depending on penetration rate (P) and external labelling (E) on highway sections with a speed limit of 100 km/h.

Regarding participants' average speed in the 80 km/h speed zone (see Figure 23), again similar emerged as reported before for 100 km/h and 130 km/h speed zones. The average speed was highest in non-automated traffic (M = 90.0 km/h), followed by the conditions with penetration rates of 25 % and 50 % automation (M = 88.4 km/h, M = 87.5 km/h). The average speed was lowest in the condition with 75 % highly automated vehicles (M = 84.4 km/h). Pairwise comparisons showed that average speed was significantly lower in the 75 % condition compared to the other three conditions (see Appendix C). Furthermore, pairwise comparisons revealed a significant difference between the condition with 0 % and 50 % automation. Regarding rule-compliance, drivers exceeded the maximum permitted speed although the average speed decreased by approximately 5 km/h to M = 84.4 km/h in the condition with 75 % highly automated vehicles compared to non-automated traffic.

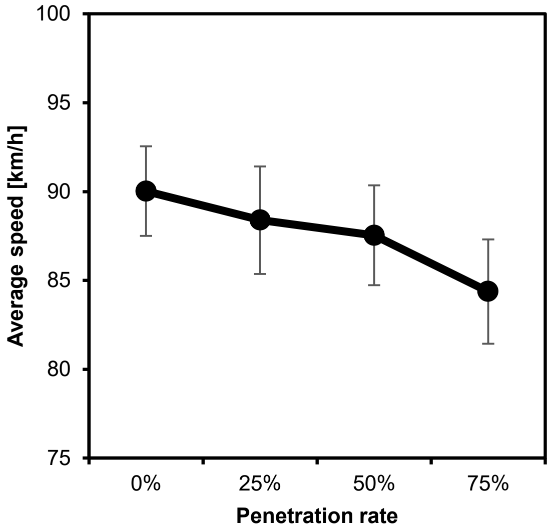


Figure 23 Average speed (means with 95 % CI) depending on penetration rate (P) and external labelling (E) on highway section with a speed limit of 80 km/h.

7.3.3.2 Safety-criticality in mixed traffic interactions

The statistical tests performed for the outcome variables mean time headway, minimum time headway and the percentage of safety-critical interactions are reported in Table 31. Table 32 provides the mean values and standard deviations for these outcome variables. The two-way ANOVAs revealed significant main effects of the within-subjects factor penetration rate on participants' mean time headway (130 km/h, 80 km/h speed zones; see Figure 24 left; see Figure 26 left) and minimum time headway (80 km/h speed zone; see Figure 26 right) as well as the percentage of safety-critical interactions (130 km/h, 100 km/h speed zones; see Figure 24 right, see Figure 25).

Table 31 Statistical tests (mixed ANOVA) for differences between experimental groups, and the penetration rate of highly automated vehicles regarding participants' mean time headway, minimum time headway and the percentage of safety-critical interactions.

		Effect	*F*	*df*	*p*	η^2_p
130 km/h	Mean time headway*	P (Penetration rate)	7.2	3,138	**< .001**	.14
		E (External labelling)	0.5	2,46	.621	
		P x E	1.2	6,138	.298	
	Minimum time headway*	P	1.1	2.7,124.0	.372	
		E	0.1	2,46	.982	
		P x E	0.9	5.4,124.0	.491	
	Percentage of safety-critical interactions*	P	3.6	1.8,81.9	**.038**	.08
		E	0.6	2,46	.552	
		P x E	0.3	3.6,81.9	.844	
100 km/h	Mean time headway***	P	0.4	3,72	.750	
		E	1.2	2,24	.329	
		P x E	1.3	6,72	.280	
	Minimum time headway***	P	1.6	3,72	.194	
		E	0.4	2,24	.669	
		P x E	1.5	6,72	.182	
	Percentage of safety-critical interactions*	P	3.0	3,138	**.034**	.06
		E	1.6	2,46	.210	
		P x E	0.4	6,138	.904	
80 km/h	Mean time headway**	P	6.1	2.7,73.8	**.001**	.19
		E	2.7	2,27	.086	
		P x E	0.5	5.5,73.8	.829	
	Minimum time headway**	P	5.5	2.7,71.6	**.003**	.17
		E	2.1	2,27	.148	
		P x E	0.2	5.3,71.6	.978	
	Percentage of safety-critical interactions*	P	2.1	2.3,106.2	.120	
		E	2.3	2,46	.115	
		P x E	1.5	4.6,106.2	.189	

***Note.* Significant p-values in bold. **N* = 49. ** *N* = 30. *** *N* = 27.**

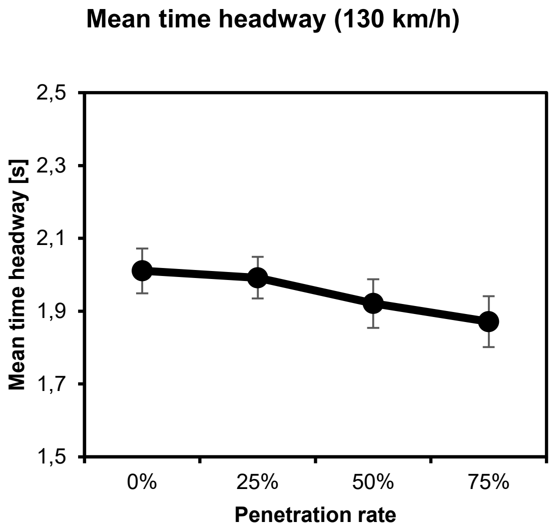
Table 32 Mean values and standard deviations including experimental groups, and the penetration rate of highly automated vehicles regarding participants' mean time headway, minimum time headway and the percentage of safety-critical interactions.

		External labelling				
		External labelling	0 %	25 %	50 %	75 %
130 km/h	Mean time headway*	With labelling	2.05 (0.22)	2.00 (0.22)	1.94 (0.14)	1.82 (0.24)
		Without labelling	2.00 (0.18)	2.05 (0.20)	1.92 (0.30)	1.92 (0.19)
		Control group	1.98 (0.24)	1.91 (0.17)	1.90 (0.24)	1.88 (0.29)
	Minimum time headway*	With labelling	0.51 (0.29)	0.53 (0.24)	0.44 (0.19)	0.58 (0.17)
		Without labelling	0.49 (0.24)	0.53 (0.24)	0.53 (0.31)	0.55 (0.20)
		Control group	0.48 (0.24)	0.42 (0.16)	0.53 (0.48)	0.57 (0.24)
	Percentage of safety-critical interactions*	With labelling	3.50 (5.20)	2.79 (2.89)	4.27 (2.88)	5.64 (8.85)
		Without labelling	2.45 (2.23)	2.47 (2.23)	4.75 (4.36)	3.83 (5.81)
		Control group	3.48 (4.00)	3.91 (3.50)	5.14 (4.58)	6.51 (8.58)
100 km/h	Mean time headway***	With labelling	2.23 (0.43)	2.25 (0.39)	2.07 (0.31)	2.02 (0.77)
		Without labelling	2.23 (0.27)	2.25 (0.66)	2.36 (0.35)	2.53 (0.34)
		Control group	2.32 (0.43)	2.28 (0.57)	2.21 (0.41)	1.86 (0.72)
	Minimum time headway***	With labelling	1.66 (0.55)	1.68 (0.46)	1.33 (0.57)	1.61 (0.92)
		Without labelling	1.32 (0.52)	1.92 (0.84)	1.52 (0.75)	2.11 (0.57)
		Control group	1.53 (0.72)	1.91 (0.73)	1.64 (0.64)	1.27 (0.71)
	Percentage of safety-critical interactions*	With labelling	0.36 (1.47)	0.52 (1.56)	3.26 (5.02)	4.55 (9.76)
		Without labelling	0.23 (0.52)	0.39 (1.46)	0.78 (1.93)	1.87 (6.09)
		Control group	1.61 (4.46)	2.29 (8.21)	3.13 (7.65)	7.21 (18.08)
80 km/h	Mean time headway**	With labelling	2.21 (0.42)	2.29 (0.27)	1.86 (0.73)	1.75 (0.37)
		Without labelling	2.41 (0.44)	2.39 (0.47)	2.42 (0.28)	2.04 (0.46)
		Control group	2.29 (0.51)	2.34 (0.46)	2.08 (0.61)	1.81 (0.57)
	Minimum time headway**	With labelling	1.47 (0.58)	1.52 (0.36)	1.35 (0.75)	0.99 (0.36)
		Without labelling	1.84 (0.80)	1.85 (0.78)	1.77 (0.49)	1.26 (0.55)
		Control group	1.77 (0.72)	1.76 (0.70)	1.41 (0.73)	1.03 (0.75)
	Percentage of safety-critical interactions*	With labelling	1.69 (4.94)	0.73 (3.00)	2.78 (6.64)	4.74 (8.60)
		Without labelling	0.66 (1.61)	2.37 (5.21)	0.00 (0.00)	1.32 (2.41)
		Control group	2.73 (6.68)	0.38 (1.54)	8.00 (15.71)	6.66 (13.91)

***Note.* *N = 49, **N = 30, ***N = 27.**

In the 130 km/h speed zone (see Figure 24 left), participants' mean time headway to preceding vehicles was highest in the 0 % condition with non-automated traffic (*M* = 2.0 s). It was followed by the conditions with 25 % and 50 % automation (*M* = 2.0 s, *M* = 1.9 s). The mean time headway was lowest in the codnition with 75 % highly automated vehicles (*M* = 1.9 s). Pairwise comparisons showed significant differences between the conditions 0 % vs. 50 % automation, 0 % vs. 75 % automation, and 25 % vs. 75 % automation (see Appendix C).

As can be seen in Figure 24 right, the percentage of safety-critical interactions with preceding vehicles in the 130 km/h zone was lowest in the condition with 25 % hihgly automated vehicles (*M* = 3.1 %). It was followed by the conditions with 0 % and 50 % automation (*M* = 3.2 %, *M* = 4.7 %). The percentage of safety-critical interactions was highest in the conditions with 75 % automation (*M* = 5.3 %). Pairwise comparisons revealed significant differences all conditions, except for 0 % vs. 25 % automation, and 50 % vs. 75 % automation (see Appendix C).



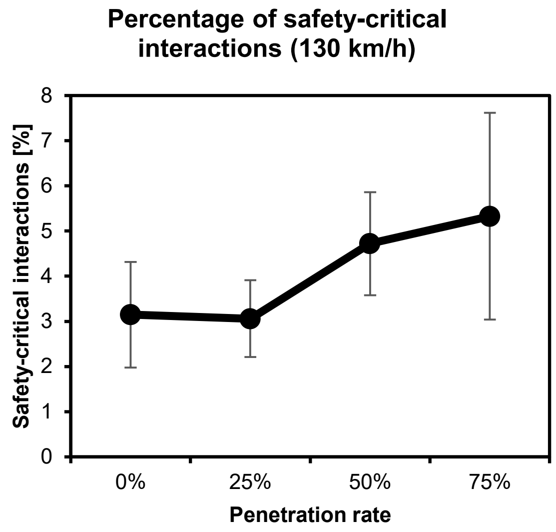


Figure 24 Left: Mean time headway (means with 95 % CI) depending on penetration rate (P) and external labelling (E) on highway section with a speed limits of 130 km/h. Right: Percentage of safety-critical interactions with preceding vehicles (means with 95 % CI) depending on penetration rate (P) and external labelling (E) on highway section with speed limit of 130 km/h.

In the 100 km/h speed zone (see Figure 25), the percentage of safety-critical interactions was lowest in 0 % condition with non-automated traffic (*M* = 0.7 %). This condition was followed by the conditions with 25 % and 50 % automation (*M* = 1.1 %, *M* = 2.4 %). The percentage of safety-critical interactions was highest in the condition with 75 % highly automated vehicles (*M* = 4.5 %). Pairwise comparisons revealed significant differences between 0 % and 75 % conditions (see Appendix C).

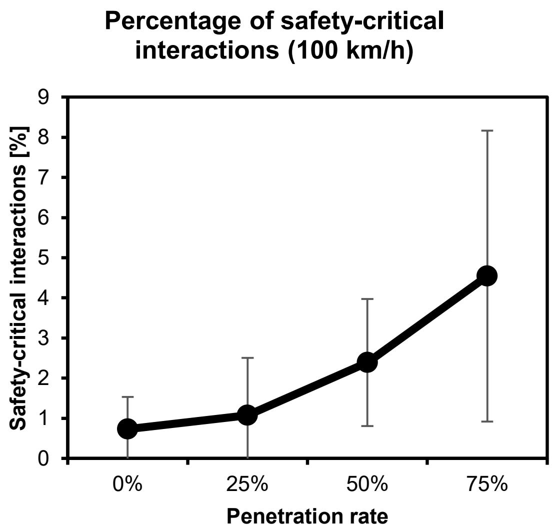


Figure 25 Percentage of safety-critical interactions with preceding vehicles (means with 95 % CI) depending on penetration rate (P) and external labelling (E) on highway section with 100 km/h speed limit.

In the 80 km/h speed zone (see Figure 26 left), participants' mean time headway to preceding vehicles was highest in the 0 % condition without mixed traffic (*M* = 2.3 s). It was followed by the 25 % and 50 % conditions (*M* = 2.3 s, *M* = 2.1 s). The mean time headway was lowest in the 75 % condition (*M* = 1.9 s). Pairwise comparisons showed significant differences between the 75% condition and the other three conditions as well as between the conditions with 25% and 50% highly automated vehicles (see Appendix C).

As can be seen in Figure 26 right, the minimum time headway was highest in the 25 % condition without mixed traffic (*M* = 1.7 s). It was followed by the 0 % and 50 % conditions (*M* = 1.7 s, *M* = 1.5 s). The minimum time headway was lowest in the conditions with 75 % hihgly automated vehicles (*M* = 1.1 s). Pairwise comparisons revealed significant differences between the 75 % condition and the other three conditions (see Appendix C).

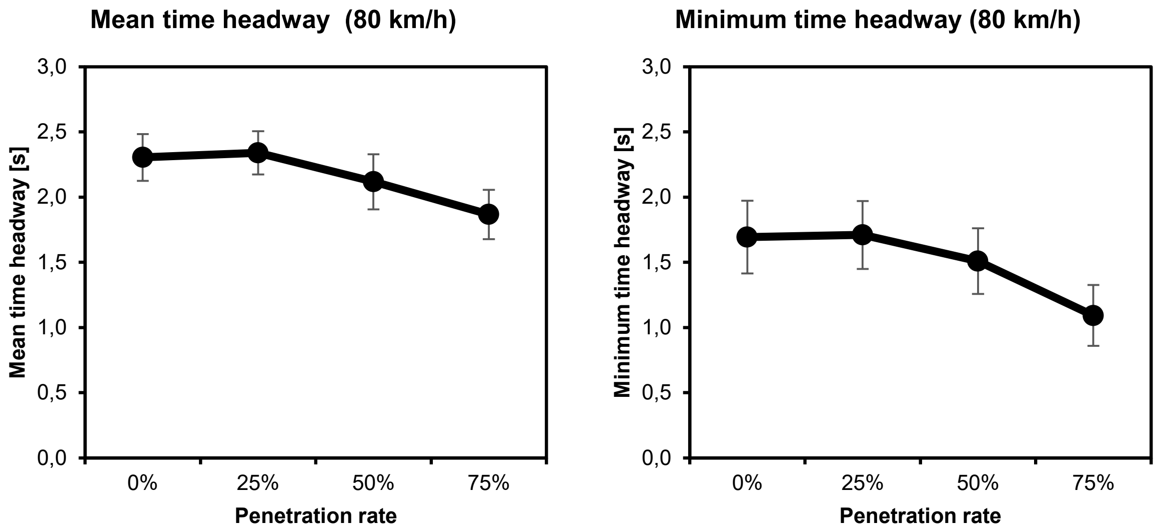


Figure 26 Left: Mean time headway (means with 95 % CI) depending on penetration rate (P) and external labelling (E) on highway section with a speed limits of 80 km/h. Right: Percentage of safety-critical interactions with automated vehicles (means with 95 % CI) depending on penetration rate (P) and external labelling (E) on highway section with speed limit of 80 km/h.

7.4 Discussion

Study 2 explored human driver reactions to highly automated vehicles in mixed traffic beyond first contact. On four 35 km long highway sections, human drivers repeatedly interacted with automated and human-driven vehicles in mixed traffic. Human driver reactions were examined depending on the type of external labelling (without labelling, with labelling, control group) and the penetration rate of highly automated vehicles (0 %, 25 %, 50 %, 75 %) on the highway sections.

After each highway section, participants in the two informed experimental groups with and without external labelling estimated the penetration rate of highly automated vehicles on the previous highway section (RQ 1). The results show that participants in the group without external labelling estimated a penetration rate of 30 % to 40 % highly automated vehicles on all four highway sections including the section with 0 % highly automated vehicles. This finding is in line with the results from Study 1 in this dissertation (see Chapter 6.3.2.1 in this dissertation) indicating that highly automated driving behavior does not necessarily have to be completely outside the range of human driving behavior. Thus, highly automated and human-driven vehicle are indistinguishable from an external perspective, supporting findings from previous research (see Stanton et al., 2020).

At the same time, this finding suggests that behavioral differences between highly automated and human-driven vehicles alone were insufficient for human drivers to distinguish these two types of vehicles in repeated interactions, contradicting the previous findings from Study 1 in this dissertation (see Chapter 6.3.1.1 in this dissertation). Following this reasoning, one may argue that human drivers do not have an adequate idea or even situation model of automated driving behavior (see Endsley, 1995a).

An alternative explanation for these supposedly contradictory findings could be the methodological differences between the two studies. Whereas Study 1 has examined human driver interactions with *one* highly automated or human-driven target vehicle at a time, the present study has focused on repeated interactions during longer trips including interactions with more than 50 highly automated and human-driven vehicles on each of the four highway sections. Therefore, the overall focus of the participants may have been less on every single vehicle interaction, but rather on making progress on the highway section. Furthermore, the human drivers observed the driving behavior of multiple simulated vehicles simultaneously for only a few moments. Thus, it reasonable to assume that this observation time may not have been sufficient to notice the implemented behavioral differences between highly automated and human-driven vehicles. At the same time, this finding highlights the importance of external labeling as a visual cue to identify the current driving mode of a vehicle supporting human drivers in estimating the penetration rate in mixed traffic correctly.

Regarding the aspects of perceived safety and comfort (RQ 2), human drivers rated driving in non-automated traffic significantly more pleasant and slightly safer than driving on highway sections in mixed traffic. Despite these differences in ratings of perceived safety between non-automated traffic and mixed traffic, the mean ratings of the three highway sections with mixed traffic are still within an acceptable range, as all mean ratings equaled to the label *very unpleasant*, ranging at the lower (positive) end of the scale of perceived safety (see Figure 18 left), and *rather pleasant* (comfort, see Figure 18 right).

As the subjective ratings in the uninformed control group were similar to the results in the other two informed groups, it is reasonable to assume the subjective ratings were based on the behavioral differences between human-driven and highly automated vehicles instead of being a product of the external labelling. At the same time, the external labelling failed to enhance human drivers' perceived safety and comfort (see Table 24), which is in line with previous findings (see Chapters 6.3.1.2 / 6.3.2.2 in this dissertation; see also GATEway project, 2017).

Regarding human drivers' emotion ratings (RQ 3), neither the increasing penetration rate of highly automated vehicles, nor the external labelling had an effect on the subjective ratings. There are several explanations for this finding. For one, it is possible that driving on highway sections may not be salient enough to elicit emotions in human drivers as there were no immediately safety-critical driving situations on the highway sections. As a result, the elicited emotions were rather weak, with anger being the most frequent and the strongest emotion (see Table 25).

In a driving simulator study, Roidl et al. (2014) found that anger could be elicited by the mere presence of other vehicles, and that anger could affect drivers' behavior even 2 km after the anger-eliciting event. So, it is possible that the highway sections in the present study were too long and the elicited emotions were rather short-lived, so that human drivers did not include the elicited emotions in their post-trial ratings. From a methodological point-of-view, it is also noteworthy that human drivers may have experienced somewhat different interactions with surrounding vehicles depending on their own driving behavior as the mixed traffic interactions on the highway sections were not standardized (see Chapter 7.5 for limitations). As a result, human drivers may have experienced different (positive or safety-critical) interactions each, which, in turn, may have elicited different emotions. As human drivers were not interviewed regarding the emotion-eliciting events after completing the highway sections, one can only speculate about the origin of the emotions. It therefore remains unclear whether emotions (positive or negative in equal measure) were elicited at all by specific features of (highly automated) driving behavior, and which situational features were involved.

After each highway section, drivers were asked how well they had progressed on the previous highway section. The results indicate that drivers had the correct impression of making significantly less progress when driving in mixed traffic compared to driving in non-automated traffic. In line with the results regarding perceived safety and comfort, this effect was evident at a penetration rate of 25 % highly automated vehicles already (see Figure 19). So, a few highly automated vehicles were already enough to create this impression. Despite the significant difference between non-automated and mixed traffic, perceived efficiency ratings still equaled to the label *rather efficient* in mixed traffic. So, it can be assumed that highly automated vehicles did not compromise human drivers too much in their general driving goal to make progress and reach their destination timely (Summala, 2007). However, it remains unclear whether there is a relationship between the impression of being slowed down and emotion ratings. It would be interesting to investigate whether anger ratings are related to the (correct) impression of being impeded by preceding highly automated vehicles, as drivers in previous research reported anger when they felt impeded in their progress by other drivers (Mesken et al., 2007). At the same time, however, the analysis of anger showed that anger was independent of the penetration rate of highly automated vehicles in the present study (see Table 27).

The driving data analyzed in the present study showed that driving in mixed traffic affected human drivers' behavior (RQ 5). For example, in the 130 km/h speed zone, human drivers' mean time headway to preceding vehicles was significantly shorter at a 50 % and 75 % penetration rate compared to non-automated traffic (see Figure 24 left). In the 100 km/h speed zone, the percentage of safety-critical time headways (< 1 s) increased, starting at a penetration rate of 50 % highly automated vehicles compared to conditions with 25 % and 0 % highly automated vehicles (see Figure 25). In the 80 km/h speed zone, minimum and mean time headways were significantly shorter in mixed traffic compared to non-automated traffic, especially in the condition with the highest penetration rate of 75 % highly automated vehicles (see Figure 26).

These findings may be explained by the behavior of the highly automated vehicles. While human-driven vehicles had a pre-defined speed of 130 km/h throughout the entire highway drive, highly automated vehicles' speed was set at speeds between 100 km/h and 110 km/h in the subsections with a speed limit of 130 km/h. In contrast, the pre-defined speed of highly automated vehicles was set to the maximum permitted speed in the subsections with lower speed limits of 100 km/h and 80 km/h. This difference in the configuration of speed shows that slower driving and the exact adherence to the speed limits make highly automated vehicles' driving style appear too slow to human drivers, resulting in close following at times. Particularly in the conditions with higher penetration rates (50 % and 75 %) of highly automated vehicles, small safety margins (< 1 s time headway) occurred increasingly frequent. In addition, participants drove significantly slower in mixed traffic compared to non-automated traffic in all three speed zones (80 km/h, 100 km/h, 130 km/h). In the speed zones with maximum permitted speeds of 80 km/h or 100 km/h respectively, human drivers drove more rule-compliant as the penetration rate of highly automated vehicles increased whereas in the 130 km/h speed zone, drivers were already driving slower than the maximum permitted speed on all highway sections. This rule-compliance in the 130 km/h speed zone could, at least in part, be explained by the experimental environment in the driving simulator as it is strenuous to drive at higher speeds in the driving simulator.

So, highly automated vehicles did contribute to reducing speed, which is a positive outcome from a traffic safety perspective. However, this speed-reducing effect cannot be attributed to the role model function of these vehicles for human drivers. If human drivers actually took an example of highly automated driving behavior and adapted their driving behavior to highly automated vehicles, they would maintain larger time headways to preceding vehicles, exercising more anticipatory driving. Instead, the short time headways found between human drivers and preceding vehicles indicate that human drivers perceive highly automated vehicles as obstacles rather than role models (RQ 4). Due to the rule-compliant and defensive driving behavior of highly automated vehicles (adhering exactly to the speed limit, driving rather slowly), safety-critical interactions with human drivers did occur. As these effects were evident in all three groups, the previous information phase in the two informed groups did not contribute to mitigate safety-criticality in mixed traffic interactions. This is in line with previous findings from Preuk et al. (2018) in car-following situations in the urban driving environment. The results from the present study might be interpreted to fuel concerns from previous literature that human drivers (may have intentions) to bully (highly) automated vehicles (e.g., Connor, 2016; Eliot, 2019; Stanton et al., 2020), but no *systematic* pattern or *intentional* bullying behavior could be discerned from the findings of the present study. In this context, it should, however, be noticed that the present study was conducted in a driving simulator and participants knew that they were being observed by the experimenter at all times. In this context, it should be noted that participants knew they were being supervised by the experimenter during the entire simulator drive so the experimental setting may have affected participants' driving behavior in a way that they were less inclined to bully highly automated vehicles. To further explore the role of external labelling in the potential bullying issue in more detail, real-world traffic seems to be a more appropriate testing environment.

Finally, the present study examined the aspect of external labelling (RQ 6) by means of three experimental groups (with external labelling, without external labelling, control group). Apart from the estimates of the penetration rates of highly automated vehicles in mixed traffic, no significant differences between the three groups were found in the present study regarding neither the subjective ratings, nor in the driving behavior on the highway sections. This finding highlights that vehicle kinematics and driving behavior are more important than the automated vehicles' external appearance, supporting the findings from previous studies and the expert interviews (see Brown & Laurier, 2017; GATEway, 2017; see Study 1 in chapter 6; see also Appendix A).

Beyond the scope of the present study, it could, however, be hypothesized that an external labelling of automated vehicle's current driving mode as a visual cue could support human drivers to better anticipate and react (more) appropriately to automated driving behavior in mixed traffic (Stanton et al., 2020). As the establishment of a mental model requires substantial learning experience over a longer period of time (see Endsley, 1995a; see also Holland et al., 1986 for more background), it is reasonable to assume that the learning time in the limited time frame of the present study was not enough to find any positive effects of the external labelling.

7.5 Limitations

The present study is subject to a number of limitations. Firstly, the number of examinable driving situations were limited. As in Study 1, the design of the highway sections was based on the expert interviews conducted in preparation (see Chapter 6.2.1; see Appendix A). So, the entire highway section was designed in such a way, that a first-generation highly automated vehicle would presumably be able to master the entire drive without sending a take-over request to its passenger. Hence, a number of common infrastructural features, e.g. construction sites and highway junctions, were excluded from the present study. At the same time, it should be noted that a complete investigation of all possible infrastructural features and driving situations on the highway was not the aim of the present study. Rather, the present study aimed to examine typical interactions between highly automated vehicles and human drivers in mixed traffic, which highly automated vehicles are very likely to be able to master independently.

Secondly, the driving behavior of the simulated highly automated vehicles on the highway sections was prototypically modeled to the assumed capabilities of a first-generation Level 3 vehicle. According to the interviewed experts, highly automated driving behavior may show manufacturer-specific differences within the legal framework (see Appendix A). Similarly, human drivers show a wide range of different driving styles (see e.g., Elander et al., 1993; Sagberg et al., 2015; Taubman-Ben-Ari et al., 2004). However, it was not possible to cover the entire range of possible highly automated and human driving styles within the scope of this study. Rather, the traffic on the highway sections as a whole aimed to simulate realistic highway traffic. Accordingly, the implemented highly automated and human driving behavior are approximations to real driving behavior. Despite the high degree of realism of the highway sections regarding the driving behavior of the simulated vehicles and the infrastructural features, it cannot be ruled out that participants may react differently to highly automated vehicles in real-world driving.

Thirdly, there was no standardization of the mixed traffic interactions on the four highway sections. Also, participants received no instructions regarding driving behavior, e.g., adherence to traffic rules. This approach enabled participants to show their natural driving behavior regarding rule-compliance, lane change behavior, speed, and safety margins to preceding vehicles. As a result, participants may have experienced different mixed traffic interactions with surrounding vehicles during the simulator drives, depending on participants' individual driving behavior, e.g., lane change behavior, and driving style including speed choice and safety margins to preceding vehicles. To some extent, this lack of standardization may have compromised the comparability of the simulator drives between participants. However, an examination of standardized mixed traffic interactions was not the goal of this study. Instead, the present study aimed to human drivers' spontaneous reactions to driving in mixed traffic in repeated interactions with highly automated vehicles. So, choosing to standardize the highway sections instead of every single interaction was advantageous to achieve more proximity to reality compared to Study 1. Taken together, the approach of the present study created an authentic experience of driving in mixed traffic for the participants.

Fourthly, participants had no personal experience with highly automated vehicles or driving in mixed traffic prior to this study as these systems are not available on the market yet (see Hetzner, 2020; Holzer, 2020). It can also be assumed that participants had different levels of knowledge about automation in general and highly automated driving on the highway in particular. Therefore, participants in the two informed experimental groups received detailed information on highly automated vehicles' driving capabilities and system limits. Thus, the information phase enabled participants to acquire some knowledge of automated driving behavior in typical driving situations on the highway before the simulator drives. Thus, the information phase helped to ensure that participants shared a common level of knowledge between participants. However, it is questionable whether the information phase compensated for the lack of personal experience with highly automated vehicles and with driving in mixed traffic in a sufficient way. As an indication of the highly automated driving mode, a blue light rectangle was used (see Figure 4). In the information phase, participants received detailed information about the function of this external HMI in the subsequent simulator study to build up prior knowledge about this highly automated driving feature as well. However, the specific eHMI design was not the subject of the present study. Instead, the design of eHMIs for the highway use-case is the subject of further research.

7.6 Conclusions

Summing up, the present study provides evidence that human drivers perceive driving on the highway in mixed traffic somewhat more unpleasant compared to driving in non-automated traffic, but not as dangerous. Furthermore, highly automated vehicles slow down human drivers, forcing human drivers to adapt their driving behavior. At lower speeds (80 km/h, 100 km/h), this has a positive impact on the driving behavior of human drivers in terms of more rule-compliance to speed limits. However, being slowed down by highly automated vehicles did result in safety-critical interactions (< 1 s time headway) with preceding vehicles. Thus, the safety-enhancing effect of speed reduction may be diminished by the risk of rear-end collisions in mixed traffic. So, highly automated vehicles have no role model function for human drivers in terms of rule-compliance and defensive driving behavior. Rather, human drivers perceive highly automated vehicles as obstacles. Beyond the scope of the present study, external labelling of the current driving mode of the highly automated vehicles could help drivers to better anticipate the behavior of the highly automated vehicles. Thus, the number of safety-critical interactions might be reduced in the long run. However, the impression of being slowed down will not be eliminated by such an external labelling.

8 Study 3 – Passing a pedestrian in longitudinal traffic

The second part of this dissertation addresses the main research question of how passengers want to be driven in a highly automated vehicle in interactions with pedestrians and cyclists in urban mixed traffic (see Chapter 5). To examine this research question, two typical space-sharing conflicts with vulnerable road users were chosen to be examined in this dissertation including an obstructed path conflict in longitudinal traffic (Study 3), and a crossing paths conflict at a junction (Study 4, see Chapter 9; Markkula et al., 2020).

8.1 Objective and research questions

In the future, human drivers will gradually become passengers (Rothenbücher et al., 2016), being driven around town automatically. In this urban driving environment, interactions with pedestrians are particularly challenging for highly automated vehicles due to the complexity of the urban infrastructure including visual obstruction and different layouts on the one hand, and the flexibility of pedestrian behavior which is difficult to predict on the other hand (Cambon de Lavalette et al., 2009; Campbell et al., 2010; Hubmann et al., 2016; Lee et al., 2020; Nolte et al., 2020; Völz, 2020).

From a technology-driven perspective, a highly automated driving function is composed of many driving parameters regarding longitudinal guidance, e.g., speed, acceleration, brake reaction, lateral guidance, and jerk, which in their combination constitute a vehicle's driving style, and thus have an impact on passenger comfort (see e.g., Bellem et al., 2018; Elbanhawi et al., 2015; see also Dettmann et al., 2021 and Ossig et al., 2021 for a review). In turn, passenger comfort will presumably be decisive for the acceptance and adoption of this new technology (Bellem et al., 2018; Siebert et al., 2013). It is therefore reasonable to assume that passengers will only use this new technology in urban mixed traffic if the highly automated system masters "standard" mixed traffic interactions with vulnerable road users successfully.

Thus, the subjective perspective of passengers as users should be taken into account in the development and specific configurations of highly automated vehicles.

Based on these considerations, Study 3 examined the main research question of how passengers want to be driven in a highly automated vehicle in urban areas. Specifically, Study 3 examined passengers' perceived risk, and comfort during a pedestrian interaction in longitudinal traffic. To this end, a driving scenario was implemented in the driving simulator which included a straight, main road with parking stands on the right-hand side and a pedestrian approaching the road, being visually obstructed by parked vehicles. In this driving scenario, passengers experienced different configurations of highly automated driving behavior including variations of *vehicle speed*, and *lateral guidance* as well as *pedestrian presence* and *oncoming traffic* (all within-subjects factors). In addition, the highly automated vehicle decelerated before pedestrian interaction in selected variations of the driving scenario. Study 3 examined the following specific research questions:

RQ 1: How do different configurations of the highly automated driving function affect passengers' perceived risk and comfort when passing a pedestrian on a parking stand?

RQ 2: How would passengers ideally want to be driven when passing a pedestrian on a parking stand?

To provide answers to these research questions, Study 3 was divided into two parts. In the first part, participants were driven automatically, experiencing a selection of pre-defined configurations of highly automated driving behavior (RQ 1). In the second part, participants were asked to drive themselves in a way that they consider ideal highly automated driving behavior in the examined driving scenario (RQ 2). This was done to validate whether the pre-defined configurations of highly automated driving behavior were acceptable for passengers, and to examine whether there are further relevant driving parameters in the highly automated driving function that may be decisive for passengers' perceived risk and comfort, but which were not covered in the first part of the present study. Due to the explorative approach of Study 3, no directed hypotheses are presented regarding these research questions.

8.2 Methods

8.2.1 Driving scenario

An urban road with one lane per direction of travel (lane width: 3.25 m per lane) and parking stands (width: 2.00 m each) on the right-hand side of the road served as the basis for the examined driving scenario (see Figure 27). A 600 m long section of the road was implemented in the driving simulator. Participants experienced the driving scenario from the passenger perspective inside the ego-vehicle. After 130 m, the highly automated ego-vehicle passed a parked vehicle on the right-hand side. In conditions, there was a pedestrian walking in the parking stand in the right-hand side as well as oncoming traffic on the left-hand side.

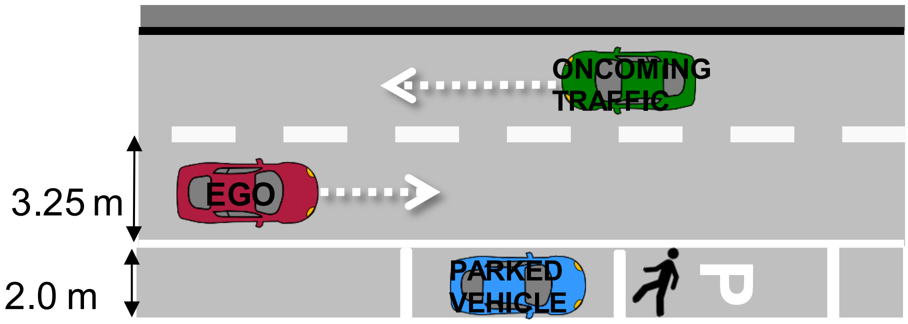


Figure 27 Driving scenario in Study 3.

This driving scenario was chosen for two reasons. Firstly, this driving scenario involves a typical interaction with a pedestrian in urban mixed traffic. Secondly, the visual obstruction of the pedestrian presents a challenge to the highly automated vehicle's trajectory planning (Nolte et al., 2018). From a technology-driven perspective, there are therefore several possibilities to design the highly automated driving function in terms of longitudinal guidance (e.g., speed, deceleration), and lateral guidance (e.g., lateral offset from the center of the lane), depending on the highly automated system's risk assessment in the driving scenario (Nolte et al., 2018).

8.2.2 Experimental design

The following section describes the experimental design for the two study parts separately. In the first part, participants were driven automatically whereas in the second part of the present study, participants were asked to drive themselves.

8.2.2.1 Study 3 Part I

The first part of the present study followed a 2 x 2 x 2 x 3 repeated-measures design (see Table 33). Regarding highly automated driving behavior, the configurations of vehicle speed, lateral guidance, and in some conditions, deceleration were varied. Vehicle speed was varied twofold (30 km/h / 50 km/h), and matched with the maximum permitted speed in the given condition of the driving scenario. Lateral guidance included three variations: (1) no lateral offset, (2) lateral offset to the left, and (3) lateral offset to the right. Lateral offsets to the right and the left included a deviation of 0.50 m from the lane's center resulting in lateral distances between 2.10 m and 1.30 m to the pedestrian behind the parked vehicle, and between 0.95 m and 1.95 m to the oncoming traffic (see Figure 28). Figure 29 shows the three variations of lateral guidance from the participant's perspective inside the highly automated ego-vehicle.

Furthermore, pedestrian presence on the parking stand (with / without pedestrian) and the presence of oncoming traffic (with / without oncoming traffic) were each varied twofold. For the oncoming traffic, the same car model was chosen for all conditions of the driving scenario to avoid confounding effects caused by potential differences in vehicle width (see Figure 28). In six selected conditions of the driving scenario (see grey markings in Table 33), the highly automated ego-vehicle decelerated before pedestrian interaction. The deceleration started at a distance of 2.4 s time headway before the parked vehicle at a deceleration rate of approximately 1.0 m/s^2, which is equivalent to human drivers taking the foot off the acceleration pedal. Vehicle speed was reduced by approximately 20 % to 24 km/h in the 30 km/h zone, and to 40 km/h in the 50 km/h zone. The ego-vehicle accelerated back to the initial speed 1 m after passing the pedestrian. To investigate the effect of the deceleration maneuver, the six conditions with deceleration were compared with the corresponding six conditions without deceleration. All participants experienced all 24 conditions of the scenario without deceleration according to the experimental design plus six additional conditions including deceleration (= 30 conditions per participant). To avoid order effects, conditions were presented in a random order.

Table 33 Experimental study design (Part I).

			Lateral offset		
Pedestrian presence	Vehicle speed	Oncoming traffic	Left	None	Right
yes	30 km/h	yes			
		no			
	50 km/h	yes			
		no			
no	30 km/h	yes			
		no			
	50 km/h	yes			
		no			

***Note.* Conditions with deceleration are marked in grey.**

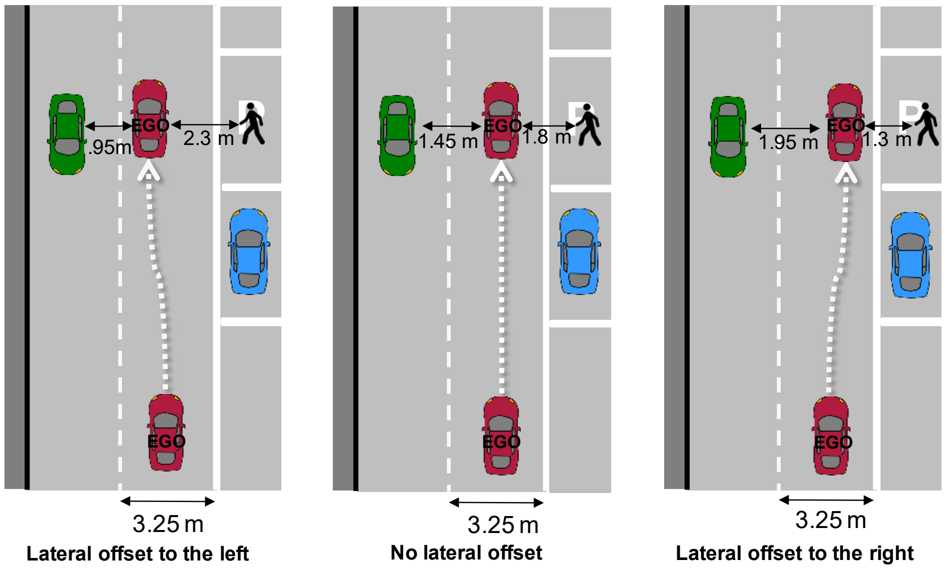


Figure 28 Left: Lateral offset to the left. Middle: No lateral offset. Right: Lateral offset to the right.

Figure 29 Lateral offset from the passenger perspective inside the highly automated vehicle. Left: Lateral offset to the left side. Right: Lateral offset to the right side.

8.2.2.2 Study 3 Part II

In the second part of the present study, participants were asked to drive themselves in a way they considered *ideal* highly automated driving behavior in the driving scenario. This was done to verify whether the configurations implemented in the first part were acceptable for passengers. In addition, this procedure allows the identification of further relevant driving parameters that may be decisive for passengers' perceived risk and comfort, but which were not covered in the first part of the present study.

Participants completed four selected conditions of the driving scenario, all including pedestrian presence. In these conditions, the maximum permitted speed (30 km/h / 50 km/h) and the presence of oncoming traffic (with / without oncoming traffic) were both varied twofold (Table 34). A pedestrian was present in all four conditions of the driving scenario. In contrast to the experimental design in the first part of the present study (see Table 33), the vehicle's *deceleration*, *lateral offset* and *vehicle speed* were subject to participants' driving behavior.

Table 34 Experimental study design and participants (Part II).

Maximum permitted speed	Oncoming traffic: yes	Oncoming traffic: no
30 km/h	32 participants	
50 km/h		

8.2.3 Dependent variables

In the first part of the present study, questionnaire data were collected and analyzed whereas in the second part, driving data were collected and analyzed.

8.2.3.1 Questionnaire data

Table 35 provides an overview over the questionnaire data collected in first part of the present study. The two items measuring passenger comfort (understandability, perceived loss of control) were used based on the Discomfort-Scale (Disco-Scale; Siebert et al., 2013). To measure perceived risk, the perceived safety scale (see Figure 6) adapted from Neukum et al. (2008) was modified by means of the following instructions:

- *Harmless* means that the experienced driving situation was not dangerous at all because the highly automated vehicle's driving behavior was neither dangerous, nor unpleasant.
- *Unpleasant* means that the driving of the highly automated vehicle in the experienced interaction was acceptable, but not ideal.
- *Dangerous* means that the driving behavior of the highly automated vehicle was still acceptable, but that participants rather not want to be a passenger being driven in this vehicle.
- *Situation not acceptable* means that a highly automated vehicle driving in this way would be absolutely inacceptable and such a vehicle should not be proved by the authorities.

Table 35 Questionnaire data collected in the first part of the present study.

Dimension	Description
Perceived risk	**Item** [1 (harmless) … 8 (situation not acceptable)]
Understandability of automated driving behavior	**Item** [1 (do not agree at all) … 5 (do fully agree)] “The automated vehicle’s driving behavior was understandable for me.”
Perceived loss of control	**Item** [1 (do not agree at all) … 5 (do fully agree)] “I felt at the mercy of the automated vehicle in the previous situation.”
Speed rating	**Item** [1 (too slow) … 7 (too fast)] “The automated vehicle was driving..."
Lateral distance to the oncoming traffic*	**Item** [1 (too small) … 7 (too large)] “The distance between the automated vehicle and oncoming traffic was...”
Lateral distance to the pedestrian*	**Item** [1 (too small) … 7 (too large)] "The automated vehicle's distance from the pedestrian on the right side of the road was..."
Lateral distance to the parking stand	**Item** [1 (too small) … 7 (too large)] "The distance from the automated vehicle to the parking stand on the right side of the road was..."

***Note.* *These outcome variables were only measured if a pedestrian or oncoming traffic was present.**

After having experienced all 30 conditions of the driving scenario, participants were asked to rate for three selected conditions of the driving scenario (see Figure 30) how dangerous and how desirable a lateral offset (lateral offset to the left / lateral offset to the right / no offset), and deceleration (with / without) are in the respective condition. In the first condition (left), there was a pedestrian on the right-hand side, but no oncoming traffic on the left-hand side. In the second condition (middle), there was oncoming traffic on the left-hand side, but no pedestrian present on the right-hand side. In the third condition (right), there was both a pedestrian on the right-hand side, and oncoming traffic on the left-hand side. The questionnaire data collected in the survey is summarized in Table 36.

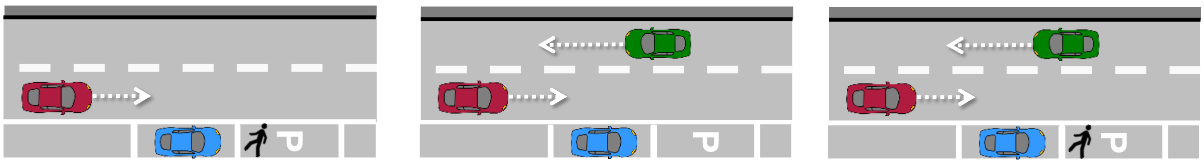


Figure 30 Conditions of the driving scenario included in the final survey. Left: Pedestrian on the right-hand side, but no oncoming traffic. Middle: Oncoming traffic, but no pedestrian presence. Right: Pedestrian on the right-hand, and oncoming traffic on the left-hand side.

Table 36 Questionnaire data collected in the final survey.

Dimension	Automated driving behavior
Desirable / dangerous Driving behavior	Lateral offset to the left Lateral offset to the right No lateral offset Deceleration No deceleration

8.2.3.2 Driving data

Table 37 provides an overview over the driving data collected in the second part of the present study. Regarding the ideal highly automated driving behavior, three aspects were analyzed, (1) vehicle speed, (2) braking, and (3) lateral offset. To this end, the positions of the pedestrian and the ego-vehicle were recorded throughout the entire simulator drive.

In order to check whether passengers want a highly automated vehicle to adapt its speed and lateral offset in the driving scenario examined, the speed and lateral offset of the vehicle were measured at two times measurement: (1) 70 m before pedestrian interaction, and (2) at the pedestrian level. To further analyze drivers' adaptation in driving behavior, the differences in speed and lateral offset between these two measurement times, i.e. before and during pedestrian interaction, were calculated.

To analyze the braking reaction, it was recorded whether passengers braked at all (yes / no), and the maximum brake reaction, which was measured using the brake pedal position.

Table 37 Driving data collected in the second part of the present study.

Measurement	Unit	Description
Vehicle speed		
Speed before pedestrian interaction	km/h	Speed 70 m before pedestrian interaction
Speed on the pedestrian level	km/h	Speed at the pedestrian level
Braking		
Maximum brake reaction	-	Maximum position of the brake pedal
Braking	Yes / No	Did participants brake?
Lateral offset		
Lateral offset in own lane before pedestrian interaction	m	Lateral deviation from the center of the lane 70 m before pedestrian interaction
Lateral offset in own lane at pedestrian level	m	Lateral deviation from the center of the lane at pedestrian level

8.2.4 Driving simulator

As Study 1 and Study 2, the present study was conducted in a fixed-base driving simulator at the Department of Traffic and Engineering Psychology at Technische Universität Braunschweig (see Chapter 6.2.3). The driving data were recorded at a rate of 60 Hz.

8.2.5 Procedure

Upon arrival, participants were acquainted with the experimental procedure and signed informed consent for the scientific use of their data. Participants were informed that they were free the drop out of the study at any point without any disadvantages. Participants then completed a sociodemographic questionnaire including questions on mobility behavior, experience with driver assistance systems and technical affinity. Next, participants were acquainted with the driving simulator. However, a training drive was not carried out prior to the first part of the study, as participants did not drive themselves, but were driven automatically. In addition, the configurations of the highly automated driving function in a training drive could have interfered with configurations tested in the subsequent driving scenario conditions.

In this first part of the study, participants' task was to observe the driving environment and the highly automated vehicle's driving behavior. After each trial, participants reached a parking stand where they completed a questionnaire on the previous drive (see Table 35). After having experienced all 30 conditions of the driving scenario, participants completed the survey (see Table 36).

In the second part of the study, participants changed from the passenger's perspective to the driver's perspective. By means of a 5-minute training drive, participants were given the chance to acquaint themselves with driving in the driving simulator. The training drive was not included in data analysis. Participants then completed four selected conditions of the driving scenario. Participants' task in this second part was to drive in a way they considered *ideal* highly automated driving behavior in this driving scenario. After having completed all four trials, participants received their reimbursement and were thanked for participation.

8.2.6 Participants

N = 34 participants took part in the present study. Participants were recruited from an internal database and a student email list. Two participants dropped out of the experiment due to motion sickness. So, the final sample consisted of *N* = 32 participants aged 18 to 85 years (*M* = 38.4 years, *SD* = 17.8 years, 16 female). On average, participants have had their driving license for 21.4 years (*SD* = 17.6 years). Almost half of the sample (44 %) had an annual mileage of more than 9000 km. Participants' technical affinity was above average with *M* = 3.88 (*SD* = 1.00) on the 6-point ATI scale (Affinity for Technology Scale; Franke et al., 2019). The majority (81 %) of participants reported that previous experience with driving assistance systems. Regarding the question how comfortable it would be to hand over the driving task to a highly automated system, 34 % of participants reported that handing over control of the driving task would be rather difficult or very difficult for them whereas 38 % of the participants stated that handing over the driving task would be rather comfortable or very comfortable. A majority of 30 (94 %) participants had previous experience with driving in the simulator, whereof 24 (75 %) had been driving in the simulator more than once before the present study.

Data collection took place in October 2019 at the Department of Traffic and Engineering Psychology at Technische Universität Braunschweig. A prerequisite for participation in this study was a valid driving license. All participants had normal or corrected-to-normal vision. The experiment lasted approximately 120 minutes per participant. Participation was reimbursed with 20 EURO. Undergraduate Psychology students at Technische Universität Braunschweig could choose between monetary reimbursement or course credit. The study was approved by the ethics committee of the Faculty of Life Sciences at Technische Universität Braunschweig.

8.2.7 Data analysis

8.2.7.1 Questionnaire data

At first, the questionnaire data from the first part of the study were analyzed. The outcome variables perceived risk, understandability, perceived loss of control, speed rating the lateral and distance to the parking stand were each analyzed by means of a 2 x 2 x 2 x 3 repeated-measures ANOVA (with post-hoc pairwise comparison). The ANOVAs included all within-subjects factors except for deceleration. All main effects and interactions effects were examined. Overall, questionnaire data from 768 simulator drives (24 conditions x 32 participants) were recorded and analyzed. There was no missing data in the analyses. For results of all pairwise comparisons for the main effects of the within-subjects factor lateral offset refer to Table D1 in Appendix D.

Subsequently, the outcome variables lateral distance to the pedestrian, and the oncoming traffic were each analyzed by means of a 2 x 3 repeated-measures ANOVA. To this end, the average of the conditions with 50 km/h and 30 km/h was calculated. The ANOVAs included all within-subjects factors except for deceleration and vehicle speed. ANOVAs were only calculated for the conditions in which a pedestrian or oncoming traffic was present. In total, questionnaire data from 384 simulator drives (12 conditions x 32 participants) was analyzed for each outcome variable. There was no missing data in the analyses.

Next, the additional six conditions of the driving scenario with deceleration were compared to the corresponding six conditions without deceleration. To this end, the average of the conditions with 50 km/h and 30 km/h was calculated (see Table D2 in Appendix D). These mean ratings were then analyzed by means of 2 x 2 x 3 repeated measures ANOVAs (with post-hoc pairwise comparison) for the outcome variables perceived risk, understandability, perceived loss of control, speed rating and the lateral distance to the parking stand. In total, questionnaire data from 384 simulator drives (6 conditions with deceleration + 6 conditions without deceleration x 32 participants) were analyzed. There was no missing data in the analyses. Regarding the investigation of the deceleration effect on the lateral distance to the oncoming traffic and the lateral distance to the pedestrian, a comparison of the conditions with and without deceleration is only meaningful in case there is a pedestrian or oncoming traffic present in the condition. Since there were only four conditions in these comparisons (2 with deceleration + 2 without deceleration; see Table 33), paired t-tests were applied to compare the conditions with and without deceleration for these two outcome variables. In total, questionnaire data from 128 simulator drives (4 conditions x 32 participants) were analyzed in the paired t-tests. There was no missing data in the analyses.

Furthermore, the deceleration was further evaluated regarding duration, strength, and onset time by means of a descriptive analysis of means and standard deviations.

Finally, the questionnaire data from the survey were analyzed by means of a descriptive analysis of frequencies.

8.2.7.2 Driving data

Overall, driving data from 128 simulator drives were recorded (4 conditions x 32 participants). To account for changes in driving behavior as a reaction to pedestrian presence, measurement time (before vs. during pedestrian interaction) was included as a within-subjects factor in the analysis. So, drivers' lateral offset, and vehicle speed were analyzed by means of 2 x 2 repeated-measures ANOVAs (with post-hoc pairwise comparisons) including the within-subjects factors *oncoming traffic* and *measurement time.* ANOVAs were carried out separately for the two speeds (30 km/h, 50 km/h). There was no missing data in the analyses. Furthermore, drivers' braking behavior was analyzed by means of a descriptive analysis of frequencies, means and standard deviations.

All means reported for Study 3 in the following results section are presented with 95% confidence intervals (CI). If the assumption of sphericity was violated, the degrees of freedom were corrected either by a Greenhouse-Geisser correction ($\varepsilon < .75$) or a Huynh-Feldt correction ($\varepsilon > .75$). For significant results of the repeated-measures ANOVAs and the paired t-tests, η^2_p and *d*, respectively, are reported as effect sizes. A significance level of $p \leq .05$ was used for all statistical tests. In regard of the exploratory approach of the study, alpha was not adjusted in order to better detect relevant effects while at the same time minimizing interpreting random variations. IBM SPSS Statistics Version 25 was used for statistical data analysis.

8.3 Results

8.3.1 Study Part I

8.3.1.1 Passengers' perceived risk

The statistical tests performed for passengers' perceived risk are reported in Table 38. Table 39 shows the mean values and standard deviations for this outcome variable. The four-way repeated-measures ANOVA revealed a significant three-way interaction between the factors pedestrian presence, lateral offset, and oncoming traffic (see Figure 31). Furthermore, there were two significant two-way interaction effects between the factors lateral offset and oncoming traffic, and between the factors lateral offset and pedestrian presence. In addition, the analysis revealed significant main effects of all four within-subjects factors on passengers' perceived risk (see Figure 32).

Table 38 Statistical tests (repeated-measures ANOVA) including all four within-subjects factors (without deceleration) regarding the outcome variable perceived risk (significant p-values in bold).

	F	*df*	*p*	η^2_{par}
Vehicle speed (S)	26.8	1,31	**< .001**	.46
Lateral Offset (L)	25.8	2,62	**< .001**	.45
Oncoming traffic (O)	32.0	1,31	**< .001**	.51
Pedestrian presence (P)	14.1	1,31	**< .001**	.31
S x L	1.2	2,62	.311	
S x O	0.3	1,31	.567	
S x P	2.3	1,31	.136	
L x O	56.1	2,62	**< .001**	.64
L x P	4.7	2,62	**.012**	.13
O x P	0.1	1,31	.807	
S x L x O	1.1	2,62	.338	
S x L x P	1.6	2,62	.213	
O x L x P	4.6	1.7,51.9	**.020**	.13
S x P x O	3.5	1,31	.073	
S x O x L x P	0.1	1.7,52.3	.956	

Table 39 Mean values and standard deviations including all four within-subjects factors (without deceleration) regarding the outcome variable perceived risk.

			Lateral offset		
Pedestrian presence	Vehicle speed	Oncoming traffic	Left	None	Right
yes	30 km/h	yes	3.44 (1.87)	1.84 (1.46)	3.28 (2.19)
		no	1.53 (1.30)	1.78 (1.41)	3.13 (2.27)
	50 km/h	yes	4.19 (2.16)	2.28 (1.89)	3.97 (2.51)
		no	2.22 (2.10)	2.63 (1.90)	4.09 (2.34)
no	30 km/h	yes	3.22 (1.66)	1.37 (0.91)	2.37 (1.74)
		no	1.25 (0.62)	1.38 (1.01)	3.03 (2.13)
	50 km/h	yes	4.41 (2.18)	1.75 (1.27)	2.84 (1.63)
		no	1.69 (1.26)	1.53 (1.05)	3.25 (1.93)

Figure 31 shows the significant three-way interaction effect between the factors pedestrian presence, lateral offset, and oncoming traffic on passengers' perceived risk. Overall, the perceived risk ratings were being located in the lower half of the scale, and ranged between the labels *harmless* and *very unpleasant*. From the passenger perspective, driving without lateral offset in the center of the lane was rated the safest configuration regarding lateral offset.

The lateral offset had ambiguous effects on passengers' perceived risk depending on the direction (right / left) and the presence of oncoming traffic. A lateral offset to the left increased passengers' perceived risk in the presence of oncoming traffic. However, if there was no oncoming traffic, a lateral offset to the left reduced passengers' perceived risk as indicated by lower mean values on the perceived risk scale. In contrast, a lateral offset to the right was rated more safety-critical compared to no lateral offset in the other conditions, also if there was neither oncoming traffic and nor a pedestrian present. Here, mean ratings ranged between the labels *medium unpleasant* and *very unpleasant*. In the condition with oncoming traffic, but without pedestrian presence, perceived risk ratings were somewhat lower than without oncoming traffic. Due to the ambiguous effect of the lateral offset on perceived risk, the two-way interactions and the main effect of lateral offset obtained in the repeated-measures ANOVA cannot be interpreted.

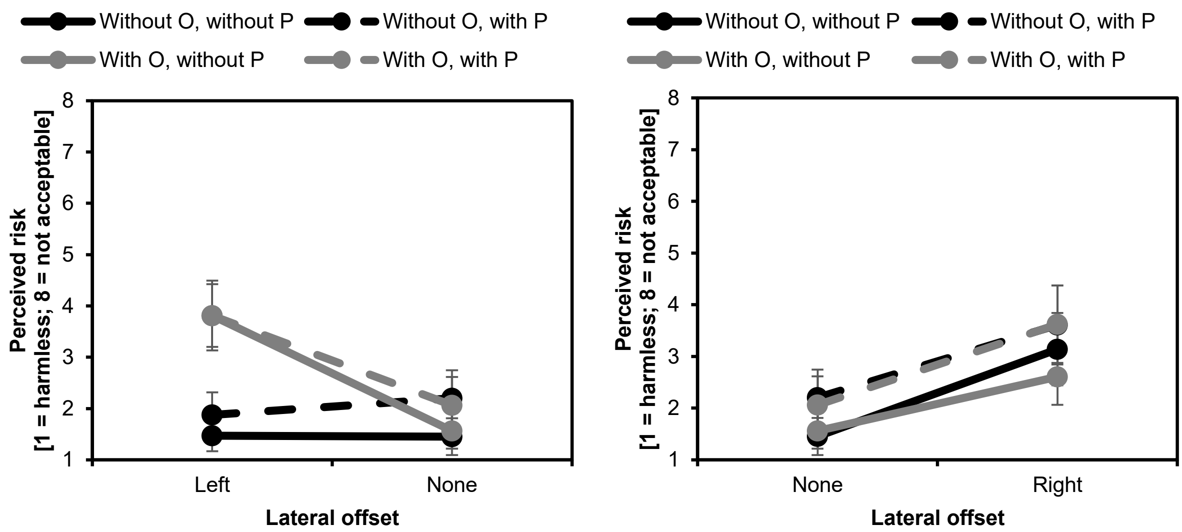


Figure 31 Perceived risk rating (means with 95 % CI) depending on oncoming traffic (O), lateral offset (L) and pedestrian presence (P). Left: Lateral offset to the left, no lateral offset. Right: Lateral offset to the right, no lateral offset.

Regarding the significant main effect of vehicle speed on perceived risk (see Figure 32), the analysis revealed that participants rated a speed of 50 km/h significantly more safety-critical compared to a speed of 30 km/h ($M_{50km/h}$ = 2.9, $M_{30km/h}$ = 2.3). The perceived risk ratings ranged between the labels *medium unpleasant* and *very unpleasant* for the two conditions of vehicle speed, with a difference of approximately 0.6 points.

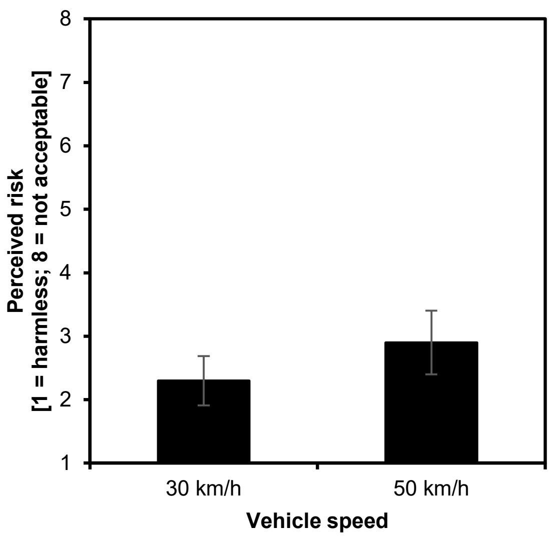


Figure 32 Perceived risk rating (means with 95 % CI) depending on vehicle speed (S).

Regarding the question whether an additional deceleration before the pedestrian interaction affected passengers' perceived risk, the analysis revealed a significant main effect of the within-subjects factor lateral offset ($F(1,31) = 8.8$, $p < .001$, $\eta^2_{par} = .22$) on perceived risk. However, there was neither a significant main effect of deceleration on passengers' perceived risk, $F(1,31) = 3.2$, $p = .084$), nor a significant interaction effect between deceleration and lateral offset on perceived risk, ($F(1.8,55.9) = 0.1$, $p = .905$). So, an additional deceleration had no effect on passengers' perceived risk (see Figure 33). Instead, the ratings of perceived risk were located in the lower half of the scale, ranging between the labels *harmless* and *very unpleasant*, regardless of the deceleration.

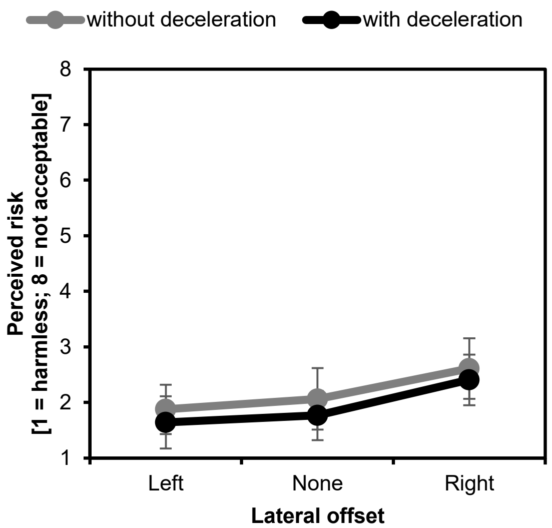


Figure 33 Perceived risk rating (means with 95% CI) depending on lateral offset (L) and deceleration (D).

8.3.1.2 Perceived loss of control

The statistical tests performed for passengers' perceived loss of control are reported in Table 40. Table 41 provides the mean values and standard deviations for this outcome variable. The four-way repeated-measures ANOVA revealed two significant two-way interaction effects between the factors lateral offset and oncoming traffic (see Figure 34 left), and between the factors lateral offset and pedestrian presence (see Figure 34 right). In addition, there were significant main effects of vehicle speed (see Figure 35), lateral offset, oncoming traffic, and pedestrian presence on passengers' perceived loss of control.

Table 40 Statistical tests (repeated-measures ANOVA) including all four within-subjects factors (without deceleration) regarding the outcome variable perceived loss of control (significant p-values in bold).

	F	*df*	*p*	η^2_{par}
Vehicle speed (S)	22.2	1,31	**< .001**	.42
Lateral Offset (L)	22.4	2,62	**< .001**	.42
Oncoming traffic (O)	30.8	1,31	**< .001**	.50
Pedestrian presence (P)	4.3	1,31	**.046**	.12
S x L	1.6	2,62	.202	
S x O	1.9	1,31	.176	
S x P	2.4	1,31	.132	
L x O	40.6	2,62	**< .001**	.57
L x P	3.8	2,62	**.027**	.11
O x P	1.0	1,31	.321	
S x L x O	0.8	2,62	.467	
S x L x P	2.5	2,62	.091	
O x L x P	1.2	1.8,57.1	.319	
S x P x O	2.3	1,31	.142	
S x O x L x P	0.4	2,62	.682	

Table 41 Mean values and standard deviations including all four within-subjects factors (without deceleration) regarding the outcome variable perceived loss of control.

			Lateral offset		
Pedestrian presence	Vehicle speed	Oncoming traffic	Left	None	Right
yes	30 km/h	yes	3.03 (1.47)	1.91 (1.38)	2.63 (1.36)
		no	1.72 (1.17)	1.84 (1.22)	2.47 (1.55)
	50 km/h	yes	3.50 (1.32)	2.09 (1.28)	3.16 (1.46)
		no	1.94 (1.27)	2.06 (1.32)	3.31 (1.42)
no	30 km/h	yes	2.87 (1.34)	1.63 (1.26)	2.38 (1.41)
		no	1.87 (1.13)	1.53 (1.11)	2.81 (1.55)
	50 km/h	yes	3.53 (1.41)	1.91 (1.33)	2.75 (1.46)
		no	2.00 (1.11)	1.62 (1.00)	2.84 (1.53)

As can be seen in Figure 34 left, the ratings of perceived loss of control were lowest if the highly automated vehicle was driving without lateral offset. In this condition, mean ratings were almost identical, regardless of the presence of oncoming traffic ($M_{without}$ = 1.8; M_{with} = 1.9). Mean ratings were similarly low if the highly automated vehicle drove a lateral offset to the left, but only if there was no oncoming traffic present at the same time (*M* = 1.9). With oncoming traffic present, however, subjective ratings were higher as passengers may want to avoid passing too close to the oncoming traffic (M = 3.2). In contrast, perceived loss of control was rated higher in the condition with a lateral offset to the right compared to the other two conditions, with mean ratings being almost identical regardless of the presence of oncoming traffic ($M_{without}$ = 2.9; M_{with} = 2.7).

Figure 34 right shows the significant two-way interaction effect between pedestrian presence and lateral offset. Overall, mean ratings were being located in the lower half of the scale. Passengers' perceived loss of control was lowest if the highly automated vehicle drove without a lateral offset in the center of the lane while at the same time, there was no pedestrian present on the parking stand (M = 1.7). With a pedestrian present, subjective ratings of perceived loss of control were somewhat higher in this condition (M = 2.0). This was followed by the condition with a lateral offset to the left. Here, mean ratings were almost identical regardless of pedestrian presence (M = 2.6; M = 2.6). Passengers' perceived loss of control was highest in the condition with a lateral offset to the right, with mean ratings being slightly higher with pedestrian presence (M = 2.9) than without pedestrian presence (M = 2.7).

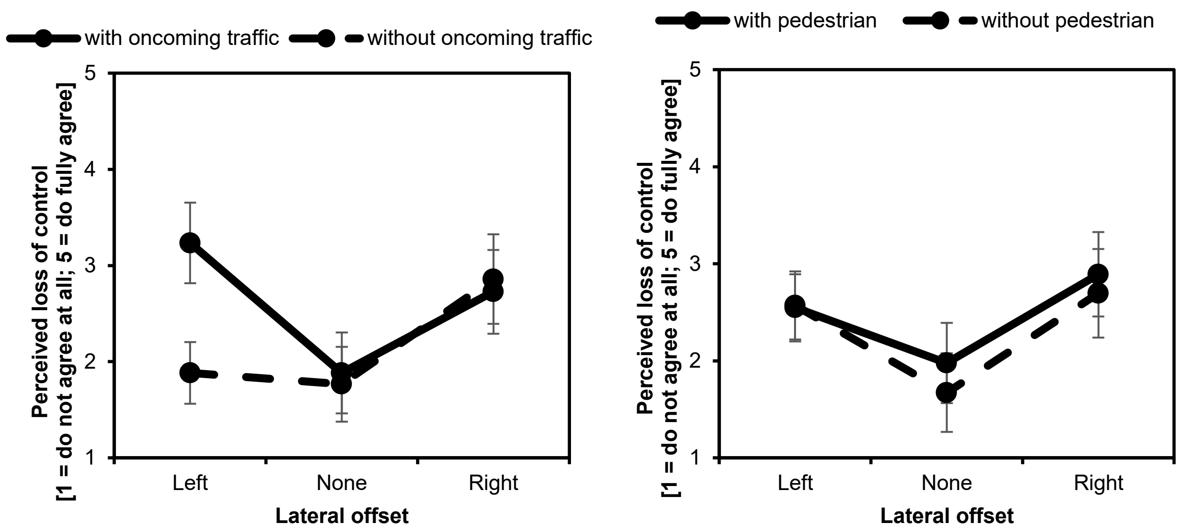


Figure 34 Left: Perceived loss of control rating (means with 95 % CI) depending on oncoming traffic (O) and lateral offset (L). Right: Perceived loss of control rating (means with 95 % CI) depending pedestrian presence (P) and lateral offset (L).

Regarding the significant main effect of vehicle speed (see Figure 35), the analysis revealed that passengers rated perceived loss of control significantly lower at a speed of 30 km/h compared to a speed of 50 km/h ($M_{30km/h}$ = 2.2, $M_{50km/h}$ = 2.6). However, the two mean ratings were both located in the lower mid-range of the rating scale, with a numerical difference of 0.4 points.

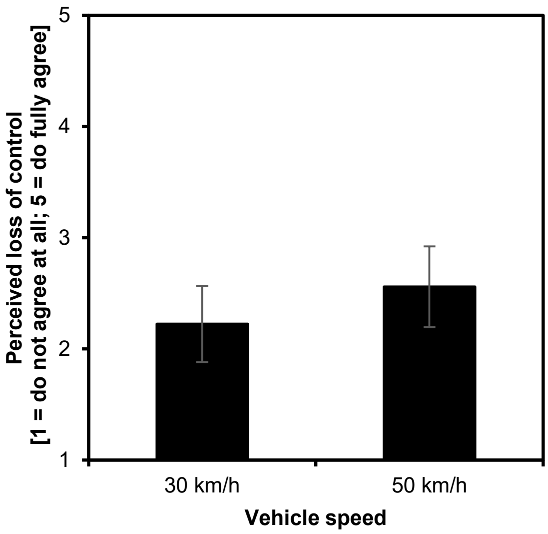


Figure 35 Perceived loss of control rating (means with 95 % CI) depending on vehicle speed (S).

Regarding the question whether an additional deceleration before the pedestrian interaction affected passengers' perceived risk, the analysis revealed significant main effects of the within-subjects factors deceleration ($F(1,31) = 4.9$, $p = .035$, $\eta^2_{par} = .14$), and lateral offset ($F(1.8,55.0) = 14.7$, $p < .001$, $\eta^2_{par} = .32$). However, there was no significant interaction effect of deceleration and lateral offset on passengers' perceived risk ($F(1.9,59.7) = 0.3$, $p = .715$). As can been seen in Figure 36, subjective ratings of perceived loss of control was significantly lower if the automated vehicle decelerated ($M = 1.9$) compared to the conditions without deceleration ($M = 2.1$). However, mean ratings differed by only 0.2 points, with perceived loss of control ratings being located in the lower end of the scale. Furthermore, passengers' rated perceived loss of control significantly higher in the condition with a lateral offset to the right ($M = 2.5$), compared to the other two conditions without lateral offset ($M = 1.9$), and a lateral offset to the left ($M = 1.8$), respectively.

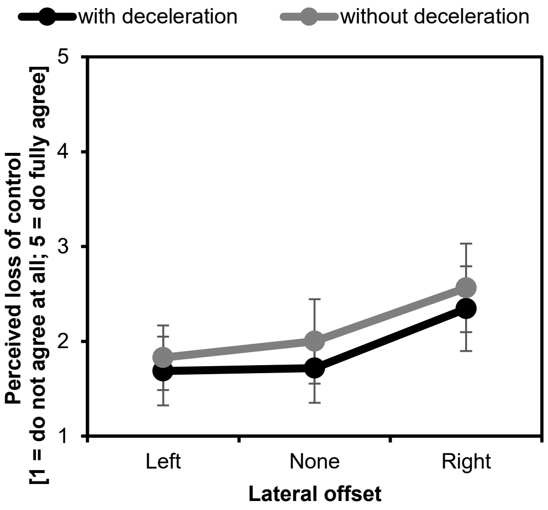


Figure 36 Perceived loss of control rating (means with 95 % CI) depending on lateral offset (L) and deceleration (D).

8.3.1.3 Understandability of automated driving behavior

The statistical tests performed for passengers' understandability of the highly automated driving behavior are reported in Table 42. Table 43 provides the mean values and standard deviations for this outcome variable. The four-way repeated-measures ANOVA revealed two significant two-way interaction effects between the factors lateral offset and oncoming traffic (see Figure 37 left), and between the factors lateral offset and pedestrian presence (see Figure 37 right). In addition, there were significant main effects of the factors vehicle speed (see Figure 38), lateral offset and oncoming traffic on the understandability of the highly automated driving behavior.

Table 42 Statistical tests (repeated-measures ANOVA) including all four within-subjects factors (without deceleration) regarding the outcome variable understandability (significant p-values in bold).

	F	*df*	*p*	η^2_{par}
Vehicle speed (S)	21.9	1,31	**< .001**	.41
Lateral Offset (L)	40.3	2,62	**< .001**	.57
Oncoming traffic (O)	30.4	1,31	**< .001**	.50
Pedestrian presence (P)	1.0	1,31	.325	
S x L	0.3	2,62	.714	
S x O	0.0	1,31	.843	
S x P	1.5	1,31	.226	
L x O	46.3	2,62	**< .001**	.60
L x P	10.1	2,62	**< .001**	.25
O x P	1.4	1,31	.253	
S x L x O	0.3	2,62	.729	
S x L x P	0.9	2,62	.426	
O x L x P	1.6	2,62	.205	
S x P x O	0.0	1,31	.849	
S x O x L x P	0.6	2,62	.568	

Table 43 Mean values and standard deviations including all four within-subjects factors (without deceleration) regarding the outcome variable understandability.

			Lateral offset		
Pedestrian presence	Vehicle speed	Oncoming traffic	Left	None	Right
yes	30 km/h	yes	2.72 (1.33)	4.03 (1.20)	2.81 (1.49)
		no	4.34 (1.04)	3.94 (1.16)	2.63 (1.56)
	50 km/h	yes	2.41 (1.24)	3.69 (1.38)	2.38 (1.39)
		no	3.88 (1.31)	3.66 (1.36)	2.13 (1.45)
no	30 km/h	yes	2.56 (1.34)	4.28 (1.17)	3.00 (1.39)
		no	3.97 (1.26)	4.50 (0.98)	2.25 (1.44)
	50 km/h	yes	2.22 (1.41)	4.12 (1.16)	2.75 (1.34)
		no	3.53 (1.27)	4.16 (1.25)	2.28 (1.40)

As can be seen in Figure 37 left, the highly automated vehicle’s driving behavior was most understandable to passengers in the conditons without a lateral offset regardless of the presence of oncoming traffic (M_{with} = 4.0; $M_{without}$ = 4.1). A lateral offset to the left was similarly understandable as driving without a lateral offset, but only when there was no oncoming traffic present at the same time (M = 3.9). In the presence of oncoming traffic, participants rated a lateral offset to the left as less understandable (M = 2.5), as passengers may want to avoid passing too close to the oncoming vehicle. A lateral offset to the right was rated as least understandable compared to the other conditions (no offset / offset to the left), being rated slightly less understandable in the presence of oncoming traffic (M = 2.3) than without oncoming traffic (M = 2.7).

Figure 37 right shows the significant two-way interaction effect between the factors lateral offset and pedestrian presence on the understandability. Again, driving without a lateral offset was best understood from the passenger's perspective, followed by an offset to the left and an offset to the right. In the condition without a lateral offset, subjective ratings of understandability were higher when there was no pedestrian present at the same time (M = 4.3), compared to the condition with pedestrian presence (M = 3.8). An offset to the left was less understandable compared to no offset, but more understandable than an offset to the right. In this condition, however, mean ratings were higher in the presence of a pedestrian (M = 3.3) than without pedestrian presence (M = 3.1). An offset to the right was rated the least understandable driving behavior, with mean ratings being almost identical in the conditions with and without pedestrian presence (M_{with} = 2.5; $M_{without}$ = 2.6).

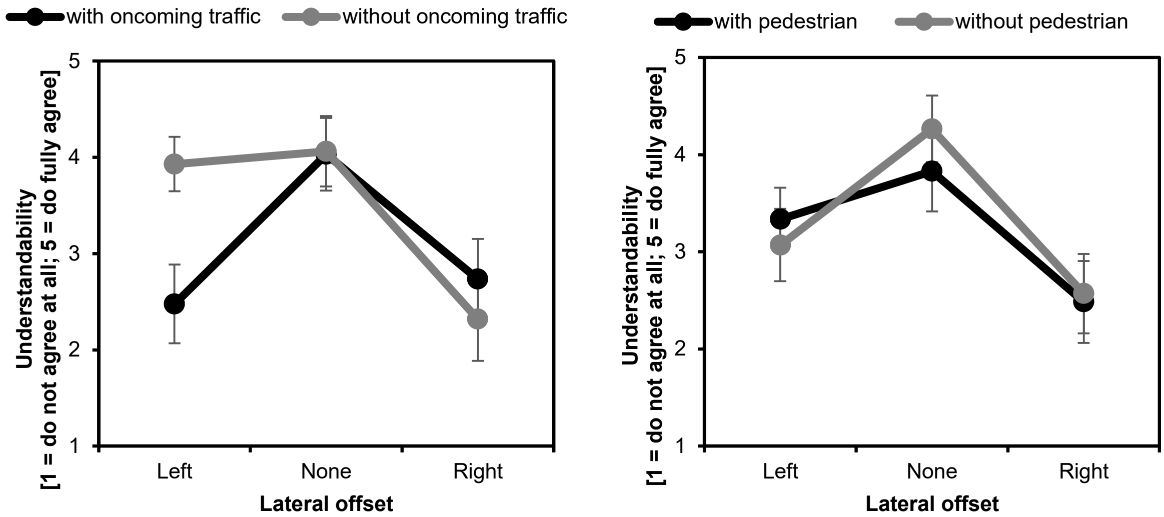


Figure 37 Left: Understandability rating (means with 95 % CI) depending on lateral offset (L) and oncoming traffic (O). Right: Understandability rating (means with 95 % CI) depending on lateral offset (L) and pedestrian presence (P).

Regarding the main effect of speed on the understandability of the highly automated driving behavior (see Figure 38), the analysis revealed that passengers rated a speed of 30 km/h significantly more understandable compared to a speed of 50 km/h ($M_{30km/h}$ = 3.4, $M_{50km/h}$ = 3.1). However, the mean ratings differed by only 0.3 points, with the two mean ratings being located in the mid-range of the rating scale.

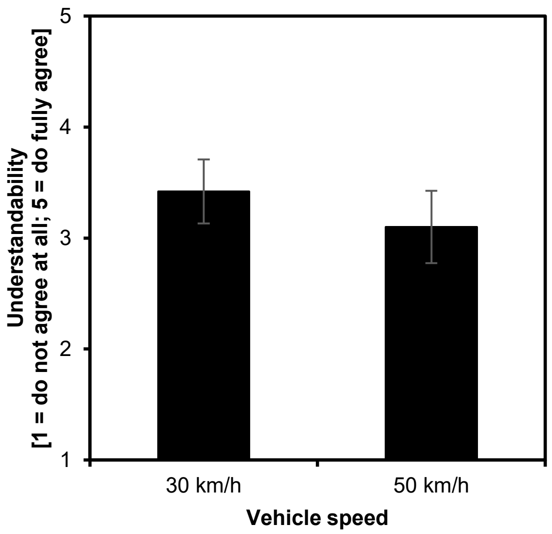


Figure 38 Understandability rating (means with 95 % CI) depending on vehicle speed (S).

Regarding the question whether an additional deceleration before the pedestrian interaction affected the understandability of the highly automated vehicle's behavior, the analysis revealed a significant main effect of the within-subjects factor lateral offset ($F(1,31) = 26.12$, $p < .001$, $\eta^2_{par} = .46$). However, there was neither a significant main effect of deceleration ($F(1,31) = 2.78$, $p = .106$), nor a significant interaction effect between deceleration and lateral offset on understandability ($F(1,31) = 0.81$, $p = .449$). So, an additional deceleration had no effect on the ratings of understandability (see Figure 39).

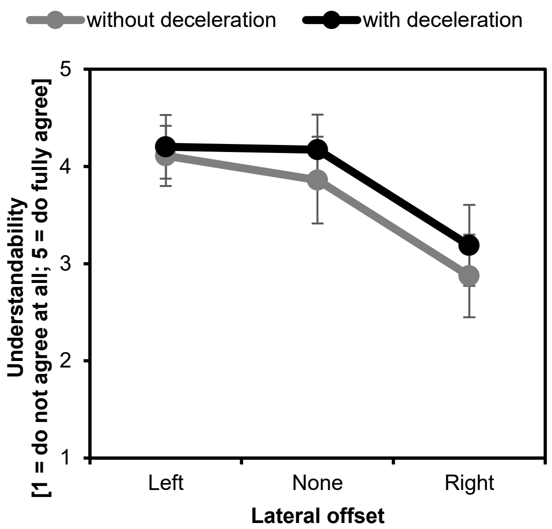


Figure 39 Understandability rating (means with 95 % CI) depending on lateral offset (L) and deceleration (D).

8.3.1.4 Speed rating

The statistical tests performed for passengers rating of the automated vehicle's speed in the driving scenario are reported in Table 44. Table 45 provides the mean values and standard deviations for this outcome variable. The analysis revealed a significant two-way interaction effect between the within-subject factors lateral offset and oncoming traffic (see Figure 40 left) as well as between speed and lateral offset (see Figure 40 right). In addition, there were significant main effects of the within-subject factors speed (see Figure 41), lateral offset, and pedestrian presence on the speed rating.

Table 44 Statistical tests (repeated-measures ANOVA) including all four within-subjects factors (without deceleration) regarding outcome variable the speed rating (significant p-values in bold).

	F	*df*	*p*	η^2_{par}
Vehicle speed (S)	38.8	1,31	**< .001**	.56
Lateral offset (L)	3.2	2,62	**.048**	.09
Oncoming traffic (O)	6.6	1,31	**.015**	.18
Pedestrian presence (P)	18.5	1,31	**< .001**	.37
S x L	3.2	2,62	**.049**	.09
S x O	1.1	1,31	.300	
S x P	3.6	1,31	.066	
L x O	7.4	2,62	**.001**	.19
L x P	0.6	1,31	.569	
O x P	0.2	1,31	.653	
S x L x O	0.0	2,62	.908	
S x L x P	0.6	2,62	.578	
O x L x P	0.8	2,62	.473	
S x P x O	3.6	1,31	.068	
S x O x L x P	0.3	2,62	.713	

Table 45 Mean values and standard deviations including all four within-subjects factors (without deceleration) regarding the outcome variable speed rating.

			Lateral offset		
Pedestrian presence	Vehicle speed	Oncoming traffic	Left	None	Right
yes	30 km/h	yes	4.19 (0.40)	3.94 (0.50)	3.91 (0.69)
		no	3.97 (0.65)	3.97 (0.40)	4.06 (0.62)
	50 km/h	yes	4.84 (1.02)	4.69 (0.82)	4.84 (1.02)
		no	4.47 (0.76)	4.56 (0.80)	4.78 (0.98)
no	30 km/h	yes	4.00 (0.25)	4.00 (0.36)	3.94 (0.56)
		no	3.75 (0.62)	3.94 (0.36)	3.94 (0.35)
	50 km/h	yes	4.56 (0.80)	4.38 (0.75)	4.56 (0.80)
		no	4.25 (0.57)	4.38 (0.66)	4.56 (0.76)

As can be seen in Figure 40 left, mean ratings were located in the mid-range of the scale, and approximately equaled to the labels *ideal* and *rather fast*. Mean ratings in two conditions without lateral offset or with lateral offset to the right were rated almost identical regardless of the presence of oncoming traffic. However, participants rated the speed of the automated vehicle with oncoming traffic as slightly faster (M_{with} = 4.4) than without oncoming traffic ($M_{without}$ = 4.1) if the automated drove a lateral offset to the left. However, these mean ratings differed by only 0.3 points with the two mean ratings being located close to the label *ideal*.

As shown in Figure 40 right, the two-way interaction between the factors vehicle speed and lateral offset seems to be very small. In the 50 km/h condition, passengers rated the automated vehicle's speed slightly higher if the vehicle drove a lateral offset to the right (M = 4.7), compared to no lateral offset (M = 4.5) and a lateral offset to the left (M = 4.5). Essentially, the analysis revealed a main effect of vehicle speed. While subjective ratings in the 30 km/h conditions was rated as *ideal* regardless of the lateral offset, a higher speed of 50 km/h was rated between the labels *ideal* and *rather fast*.

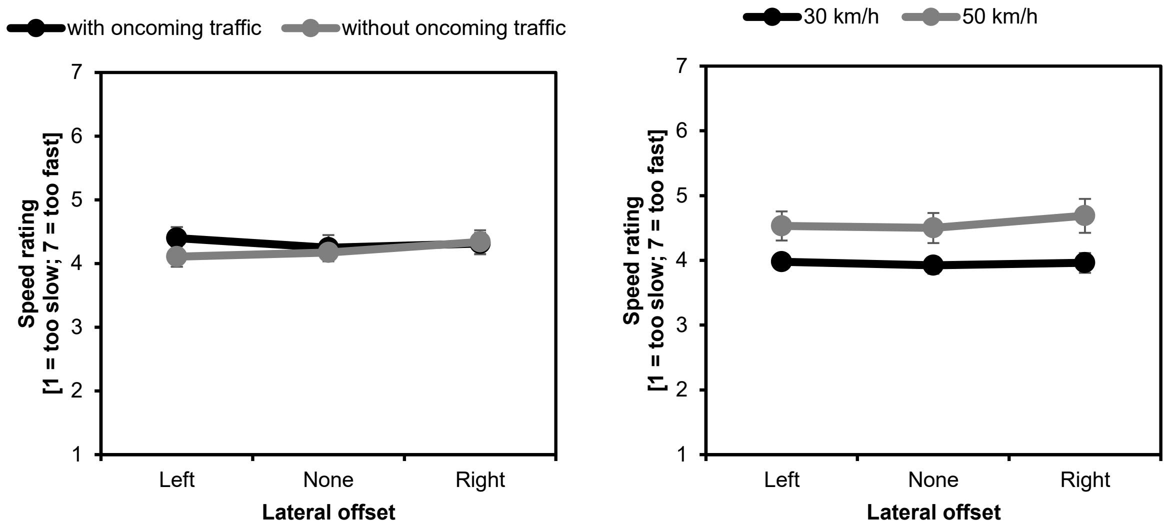


Figure 40 Left: Speed rating (means with 95 % CI) depending in lateral offset (L) and oncoming traffic (O). Right: Speed rating (means with 95 % CI) depending on lateral offset (L) and vehicle speed (S).

Regarding the main effect of pedestrian presence on the speed rating (see Figure 41), participants rated the highly automated vehicle's speed significantly faster in the condition with pedestrian presence (M_{with} = 4.4) compared to the condition without pedestrian presence (M_{without} = 4.2). Although subjective ratings were significantly closer to the label *ideal* in the condition without pedestrian presence, mean ratings between the two conditions differed by only 0.2 points.

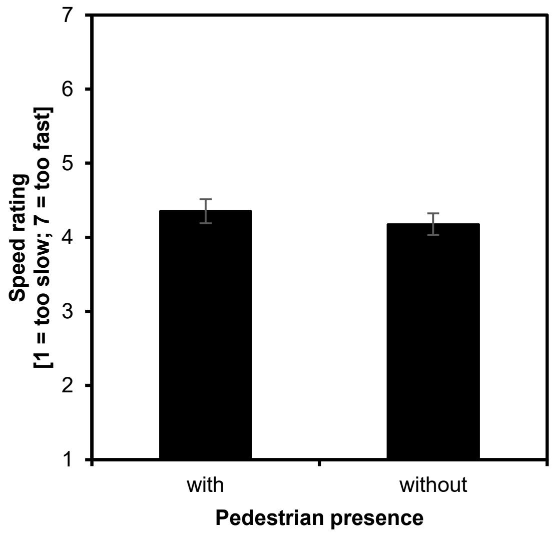


Figure 41 Speed rating (means with 95 % CI) depending on pedestrian presence (P).

Regarding the question whether an additional deceleration before the pedestrian interaction affected passengers' speed rating, the analysis revealed neither significant main effects of deceleration (F(1,31) = 0.01, p = .914), and lateral offset (F(1,31) = 1.71, p = .189), nor an interaction effect between the two factors (F(1,31) = 2.17, p = .123). As can be seen in Figure 42, an additional deceleration had no effect on the speed rating. Overall, all mean ratings of speed ranged between the labels *ideal* and *rather fast* regardless of lateral offset and deceleration.

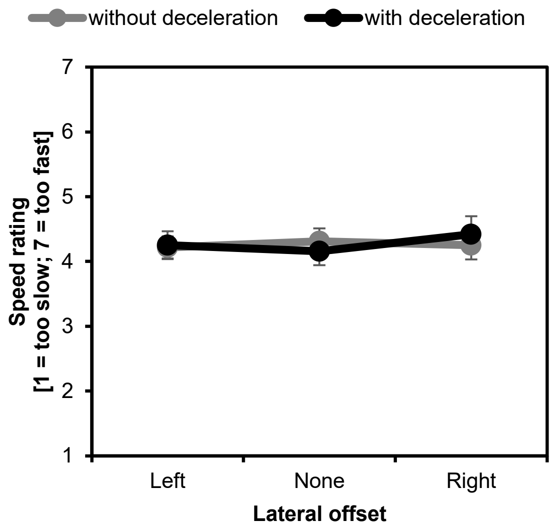


Figure 42 Speed rating (means with 95 % CI) depending on lateral offset (L) and deceleration (D).

8.3.1.5 Lateral distance to the parking stand

The statistical tests performed for participants' rating of the lateral distance to the parking stand are reported in Table 46. Table 47 provides the mean values and standard deviations for this outcome variable. The analysis revealed a significant two-way interaction effect between the factors lateral offset and pedestrian presence (see Figure 43). Furthermore, there were significant main effects of the factors lateral offset and oncoming traffic on the lateral distance to the parking stand (see Figure 44).

Table 46 Statistical tests (repeated-measures ANOVA) including all four within-subjects factors (without deceleration) regarding the outcome variables lateral distance to the parking stand (significant p-values in bold).

	F	*df*	*p*	η^2_{par}
Vehicle speed (S)	.05	1,31	.826	
Lateral offset (L)	123.9	1.2,36.6	**< .001**	.80
Oncoming traffic (O)	11.3	1,31	**.002**	.27
Pedestrian presence (P)	1.1	1,31	.312	
S x L	2.1	1.8,54.3	.134	
S x O	.03	1,31	.858	
S x P	0.3	1,31	.595	
L x O	3.0	1.9,57.6	.061	
L x P	16.8	1.6,50.1	**< .001**	.35
O x P	0.7	1,31	.401	
S x L x O	1.5	1.6,50.2	.224	
S x L x P	0.2	2,62	.860	
O x L x P	1.1	1.4,44.4	.312	
S x P x O	0.3	1,31	.581	
S x O x L x P	0.9	1.6,48.6	.384	

Table 47 Mean values and standard deviations including vehicle speed, lateral offset, oncoming traffic, and pedestrian presence (without deceleration) regarding the outcome variables lateral distance to the parking stand.

			Lateral offset		
Pedestrian presence	Vehicle speed	Oncoming traffic	Left	None	Right
yes	30 km/h	yes	4.69 (0.86)	3.97 (0.31)	2.88 (1.13)
		no	4.44 (0.62)	3.84 (0.52)	2.88 (1.16)
	50 km/h	yes	4.91 (1.09)	3.78 (0.61)	2.91 (1.30)
		no	4.41 (0.71)	3.87 (0.66)	2.75 (1.14)
no	30 km/h	yes	4.88 (0.83)	4.00 (0.44)	2.63 (1.10)
		no	4.72 (0.68)	3.88 (0.42)	2.16 (1.11)
	50 km/h	yes	5.19 (1.00)	3.88 (0.49)	2.50 (1.11)
		no	4.78 (1.01)	3.81 (0.47)	2.31 (1.06)

As can be seen in Figure 43, participants rated the lateral distance to the parking stands nearly *ideal* in the conditions where the automated vehicle was driving without lateral offset regardless of pedestrian presence (M_{with} = 3.9, $M_{without}$ = 3.9). On the contrary, a lateral offset to the left was rated larger, with mean values being located between the labels *ideal* and *rather large*. In this condition, participants rated the distance without pedestrian presence ($M_{without}$ = 4.9) larger than with pedestrian presence (M_{with} = 4.6). In contrast, a lateral offset to the right was rated on average between the labels *rather small* and *small*. In this condition, the distance was rated slightly larger with pedestrian presence (M_{with} = 2.9) than without pedestrian presence ($M_{without}$ = 2.4).

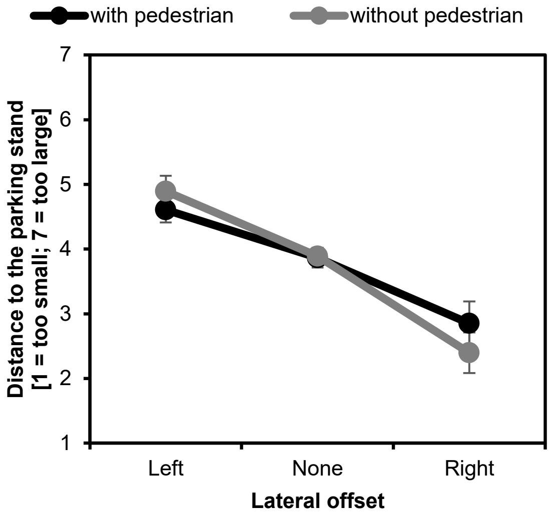


Figure 43 Distance to the parking stand rating (means with 95 % CI) depending on lateral offset (L), and pedestrian presence (P).

As can be seen in Figure 44, participants rated the lateral distance of the highly automated vehicle to the parked vehicle on the right hand slightly larger in the condition with oncoming traffic than without oncoming traffic (M_{with} = 3.9, M_{without} = 3.7). However, the mean ratings in the two conditions were both being located close to the label *ideal*.

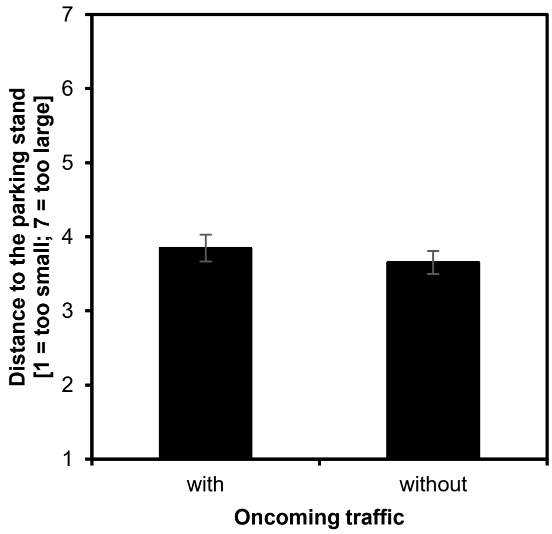


Figure 44 Distance to the parking stand rating (means with 95 % CI) depending on oncoming traffic (O).

Regarding the question whether an additional deceleration before the pedestrian interaction affected passengers' rating of the lateral distance to the parking stand, the analysis revealed a significant interaction effect between deceleration, and lateral offset (F(1.4,44.3) = 96.4,

$p < .001$, $\eta^2_{par} = .76$) as well as main effects of deceleration ($F(1,31) = 20.1$, $p < .001$, $\eta^2_{par} = .39$) and lateral offset ($F(1.6,50.4) = 6.8$, $p = .004$, $\eta^2_{par} = .18$).

In the condition with a lateral offset to the left (see Figure 45), passengers rated the lateral distance to the parking stand smaller if the vehicle decelerated before pedestrian interaction ($M = 3.7$) compared to the condition with deceleration ($M = 4.2$), with the two mean ratings being located close to the label *ideal*. In the condition without a lateral offset, the distance to the parking stand was rated nearly *ideal* ($M_{without} = 3.9$, $M_{with} = 4.0$), regardless of the deceleration. The direction of effect changed if the automated vehicle drove an offset to the right. In this condition, subjective ratings ranged between the labels *ideal*, and *rather large* if the automated vehicle decelerated ($M = 5.0$) whereas subjective ratings ranged between the labels *rather small* and *small* ($M = 2.6$).

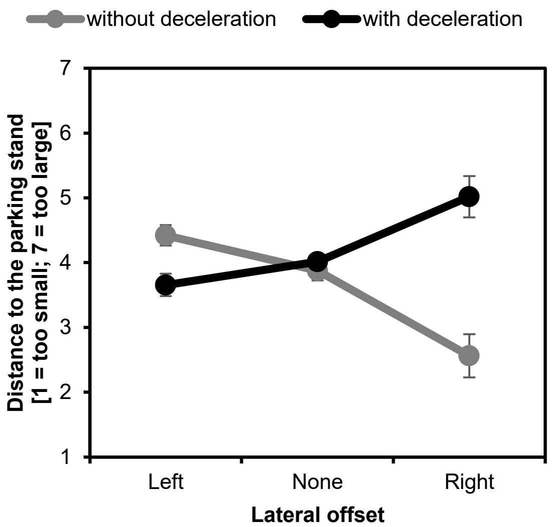


Figure 45 Distance to the parking stand rating (means with 95 % CI) depending on lateral offset (L), and deceleration (D).

8.3.1.6 Lateral distance to the pedestrian

The statistical tests performed for passengers rating of the lateral distance to the pedestrian are reported in Table 48. Table 49 provides the mean values and standard deviations for this outcome variable. The analysis revealed significant main effects of all within-subjects factors (see Figure 46 left, right; see Figure 47). There were no significant interaction effects found in the analysis.

Table 48 Statistical tests (repeated-measures ANOVA) including vehicle speed, oncoming traffic, and lateral offset (without deceleration) regarding the outcome variable lateral distance to the pedestrian (significant p-values in bold).

	F	*df*	*p*	η^2_{par}
Vehicle speed (S)	8.1	1,31	**.008**	.21
Lateral offset (L)	64.7	1.4,45.5	**< .001**	.68
Oncoming traffic (O)	15.7	1,31	**< .001**	.34
S x L	1.2	2,62	.302	
S x O	0.2	1,31	.631	
L x O	0.3	1.8,57.2	.731	
S x L x O	0.4	1.7,52.9	.661	

Table 49 Mean values and standard deviations including vehicle speed, lateral offset, oncoming traffic, and pedestrian presence (without deceleration) regarding the lateral distance to the pedestrian.

		Lateral offset		
Vehicle speed	Oncoming traffic	Left	None	Right
30 km/h	yes	4.44 (0.98)	3.66 (0.70)	2.84 (1.32)
	no	4.09 (0.69)	3.41 (0.88)	2.56 (1.13)
50 km/h	yes	4.25 (1.02)	3.37 (0.83)	2.53 (1.24)
	no	4.13 (0.71)	3.22 (0.94)	2.16 (1.22)

As can be seen in Figure 46 left, passengers rated the lateral distance to the pedestrian significantly larger at a speed of 30 km/h (*M* = 3.5) compared to a speed of 50 km/h (*M* = 3.3). Similarly, passengers rated the distance to the pedestrian with oncoming traffic (*M* = 3.5) significantly larger than without oncoming traffic (*M* = 3.3, see Figure 46 right). All mean ratings were located between the labels *rather small* and *ideal*, with a numerical difference of approximately 0.2 points.

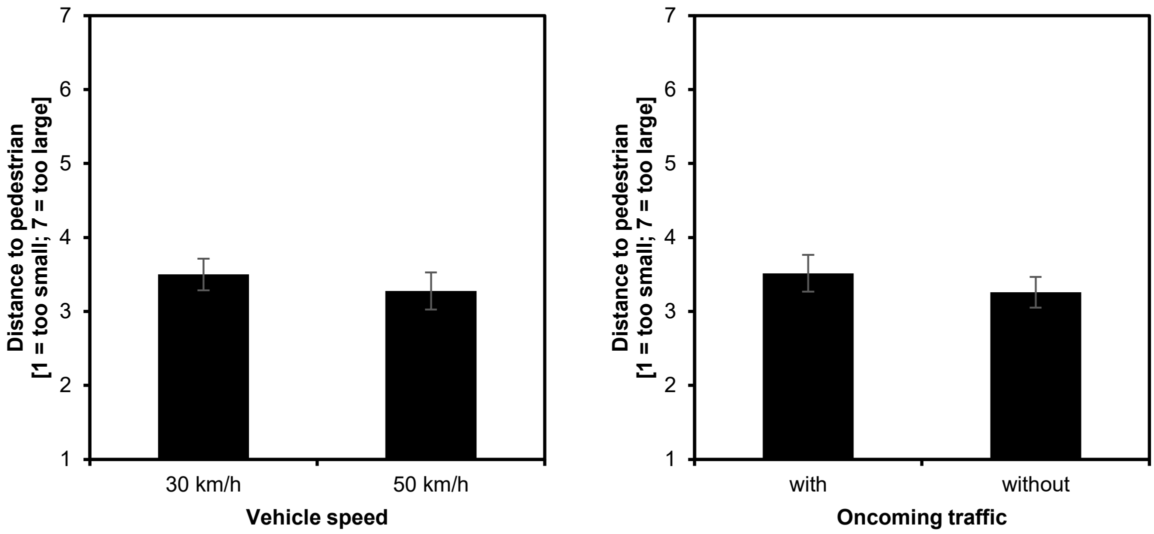


Figure 46 Left: Distance to pedestrian rating (means with 95 % CI) depending on vehicle speed (S). Right: Distance to pedestrian rating (means with 95 % CI) depending on oncoming traffic (O).

Regarding the significant main effect of the within-subjects factor lateral offset (see Figure 47), participants rated the distance to the pedestrian between *ideal* and *rather large* in the condition with a lateral offset to the left (M = 4.2), between *ideal* and *rather small* in the condition without lateral offset (M = 3.4), and between *rather small* and *small* in the condition with lateral offset to the right (M = 2.5). Pairwise comparisons revealed significant differences between all three conditions (all ps < .001).

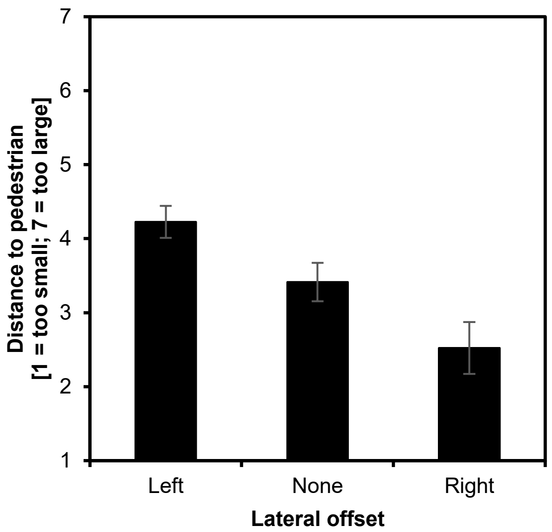


Figure 47 Distance to pedestrian rating (means with 95 % CI) depending on lateral offset (L).

Regarding the question of how the deceleration before the pedestrian interaction affected passengers' ratings of the lateral offset to the pedestrian, the two pairwise comparisons (paired-samples t-tests; see Table 33) yielded opposite results. In the first pairwise comparison (without lateral offset, oncoming traffic present), passengers rated the lateral distance to the pedestrian as significantly larger if the highly automated vehicle decelerated before the pedestrian interaction (t(1,31) = 3.56, p = .001). The mean rating in the condition with deceleration (M = 4.2) was close to the label *ideal* while the lateral distance to the pedestrian without deceleration was rated as significantly smaller (M = 3.5).

In the second pairwise comparison (no oncoming traffic, lateral offset to the left), passengers rated the lateral distance to the pedestrian significantly larger without deceleration (M = 4.1) compared to the condition with deceleration (M = 3.8; t(1,31) = 2.13, p = .041). Although the numerical difference between the two conditions with and without deceleration was significant with a difference of approximately 0.3 scale points, with the two mean ratings being located close to the label *ideal*.

8.3.1.7 Lateral distance to oncoming traffic

The statistical tests performed for passengers ratings of the lateral distance to the oncoming traffic are reported in Table 50. Table 51 provides the mean values and standard deviations for this outcome variable. The four-way repeated-measures ANOVA revealed a significant two-way interaction effect between the factors lateral offset and vehicle speed. Furthermore, there were significant main effects of the within-subjects factors lateral offset and vehicle speed (see Figure 48). No further significant interaction effects or main effects were found in the analysis.

Table 50 Statistical tests (repeated-measures ANOVA) including speed, lateral offset and pedestrian presence (without deceleration) regarding the lateral distance to the oncoming traffic (significant p-values in bold).

	F	*df*	*p*	η^2_{par}
Vehicle speed (S)	7.2	1,31	**.011**	.19
Lateral offset (L)	195.9	1.4,43.3	**< .001**	.86
Pedestrian presence (P)	0.4	1,31	.540	
S x L	5.9	1.6,49.3	**.009**	.16
S x P	0.1	1,31	.781	
L x P	0.2	1.7,53.7	.821	
S x L x P	2.4	1.9,58.4	.100	

Table 51 Mean values and standard deviations including vehicle speed, lateral offset and pedestrian presence (without deceleration) regarding the lateral distance to the oncoming traffic.

		Lateral offset		
Pedestrian presence	Vehicle speed	Left	None	Right
yes	30 km/h	2.25 (0.98)	3.84 (0.45)	4.69 (1.09)
	50 km/h	1.81 (0.86)	3.94 (0.67)	4.53 (1.08)
no	30 km/h	2.25 (0.92)	3.84 (0.52)	4.50 (0.84)
	50 km/h	1.72 (0.77)	3.75 (0.51)	4.72 (1.02)

As Figure 48 shows, subjective ratings of the lateral distance to the oncoming traffic differed depending on the highly automated vehicle’s lateral offset and vehicle speed. Driving without lateral offset was rated almost *ideal* ($M_{30\ km/h}$ = 3.9, $M_{50\ km/h}$ = 3.9) while the mean ratings for an offset to the right ranged between the labels *ideal* and *rather large,* regardless of the driven speed ($M_{30\ km/h}$ = 4.6, $M_{50\ km/h}$ = 4.6). In contrast, passengers rated the distance to the oncoming traffic in the condition with a lateral offset smaller compared to the other two offset conditions. In addition, subjective ratings were speed-dependent, with the lateral distance to the oncoming traffic being rated smaller at a speed of 50 km/h (*M* = 1.8) compared to a speed of 30 km/h (*M* = 2.3).

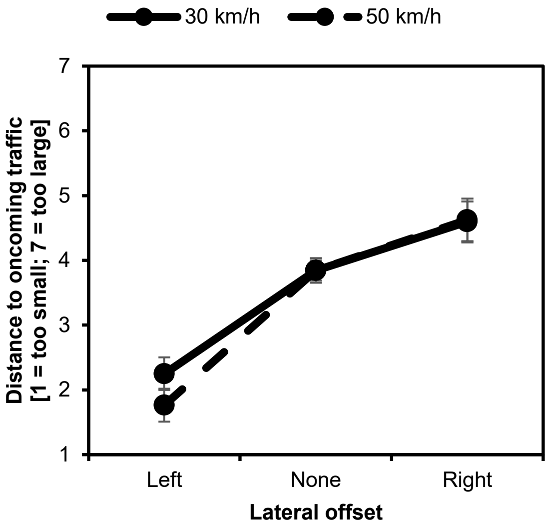


Figure 48 Distance to oncoming traffic rating (means with 95 % CI) depending on lateral offset (L), and vehicle speed (S).

Regarding the question of whether a deceleration before pedestrian interaction affected passengers' ratings of the lateral distance to oncoming traffic, the two pairwise comparisons (t-tests for paired samples) yielded opposite results. In the first pairwise comparison (no lateral offset, with pedestrian presence), a deceleration had no effect on the mean ratings of the lateral distance to oncoming traffic ($t(1,31) = 1.64$, $p = .111$). Mean ratings were close to the label *ideal* in the two conditions ($M_{with} = 3.9$; $M_{without} = 4.1$).

In the second pairwise comparison (lateral offset to the right, no pedestrian presence), passengers rated the lateral distance to oncoming traffic significantly larger in the condition without deceleration ($M = 4.6$) than with deceleration ($M = 3.5$; $t(1,31) = 4.62$, $p < .001$).

8.3.1.8 Deceleration

As can be seen in Figure 49, participants rated the automated vehicle's deceleration regarding the aspects (1) onset time, (2) duration, and (3) strength as almost ideal (= 4).

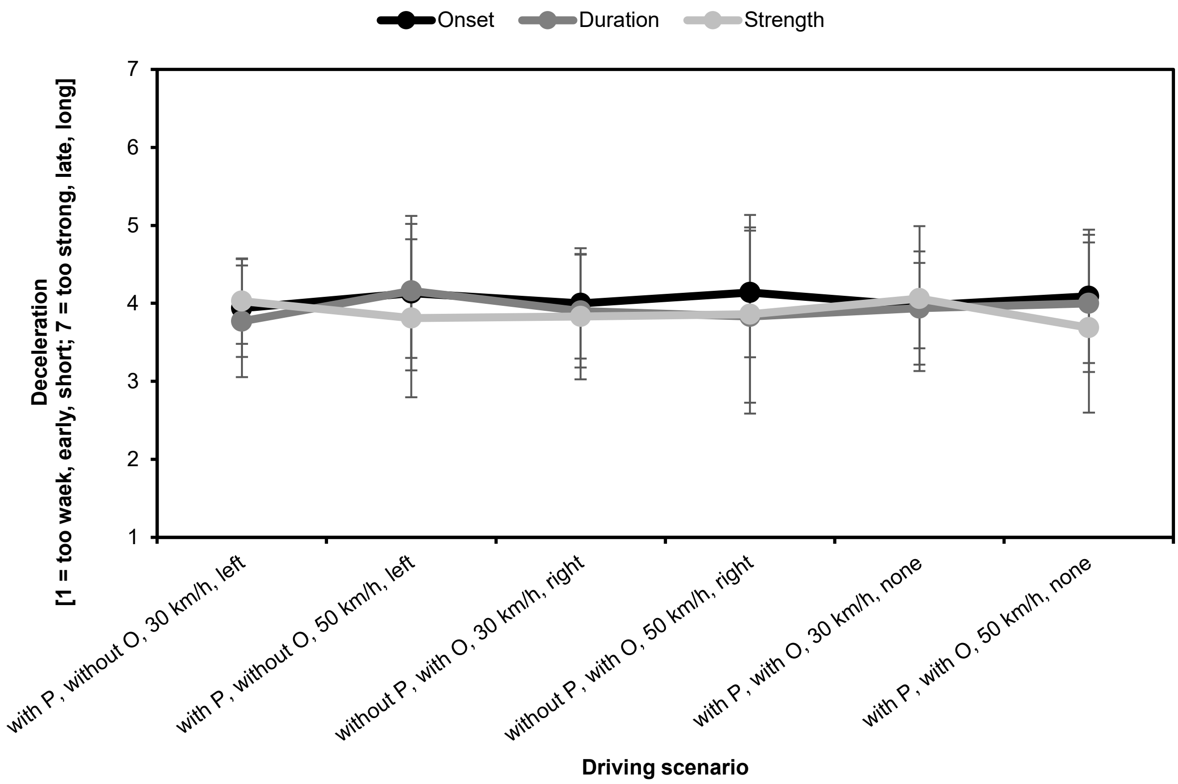


Figure 49 Deceleration ratings (means with standard deviations) depending on pedestrian presence (P), oncoming traffic (O), vehicle speed (S) and lateral offset (L).

8.3.1.9 Survey

After having completed the first part of the present study, participants rated how dangerous and how desirable they consider a lateral offset (to the left / to the right / no offset), and braking (deceleration / no deceleration) in three selected conditions of the examined driving scenario (see Figure 30).

In the first condition of the driving scenario with pedestrian presence on the right-hand side, but without oncoming traffic, half of the participants (56 %) rated a lateral offset to the left desirable driving behavior. Another 14 (44 %) participants considered driving without an offset desirable. In contrast, a majority of 29 (91 %) participants considered a lateral offset to the right towards the pedestrian a dangerous maneuver.

Furthermore, 20 (63 %) participants rated braking desirable whereas a minority of 9 % of the participants rated this behavior dangerous. Half of the participants (53 %) considered no deceleration dangerous in this situation. In contrast, 25 % of participants, preferred no deceleration. The results are summarized in Figure 50.

Figure 50 Desirable and dangerous driving behavior in the first condition of the driving scenario.

In the second condition of the driving scenario with oncoming traffic, but without pedestrian presence (see Figure 51), all (100%) participants rated driving without a lateral offset desirable. In contrast, 31 (97 %) participants rated a lateral offset to the left and 22 (69 %) participants an offset to the right dangerous.

Regarding deceleration, passengers' preferences were ambiguous. While 11 (34 %) participants considered a deceleration before pedestrian interaction desirable, 8 (22 %) passengers rejected this behavior. At the same time, 13 (41 %) participants rated no deceleration desirable while 11 (34 %) participants considered this behavior dangerous.

Figure 51 Desirable and dangerous driving behavior in the second condition of the driving scenario.

The third condition of the driving scenario with oncoming traffic and pedestrian presence (see Figure 52), participants showed a clear preference for driving without a lateral offset (94 %). In contrast, a lateral offset to the left or right was considered dangerous by a large majority (91 % / 94 %) of participants. In addition, there was a clear preference for deceleration. 23 (72 %) participants rated this behavior desirable, only 9 % of participants considered this behavior dangerous.

Figure 52 Desirable and dangerous driving behavior in the third condition of the driving scenario.

8.3.2 Study Part II

8.3.2.1 Speed change

The statistical tests performed for the outcome variable speed change (before vs. during pedestrian interaction) are reported in Table 52, separately for the 30 km/h and 50 km/h conditions. Table 53 provides the mean values and standard deviations for this outcome variable. The two-way ANOVA revealed a significant main effect of the factor measurement time in the 30 km/h condition (see Figure 53) on the speed change.

Table 52 Statistical tests (repeated-measures ANOVA) including the within-subjects factors measurement time and oncoming traffic regarding speed change (before vs. during pedestrian interaction).

		Effect	*F*	*df*	*p*	η^2_{par}
Speed change	30 km/h	Measurement time (T)	16.1	1,31	**< .001**	.34
		Oncoming traffic (O)	0.5	1,31	.500	
		T x O	0.8	1,31	.372	
	50 km/h	T	2.7	1,31	.108	
		O	0.1	1,31	.759	
		T x O	2.2	1,31	.146	

Table 53 Mean values and standard deviations including the within-subjects factors measurement time and oncoming traffic regarding speed change (in km/h).

		Oncoming traffic	
	Maximum permitted speed	yes	no
Speed before pedestrian interaction	30 km/h	31.38 (2.95)	31.24 (3.51)
	50 km/h	47.76 (4.45)	47.17 (4.60)
Speed during pedestrian interaction	30 km/h	27.27 (5.46)	28.24 (5.62)
	50 km/h	48.12 (3.27)	49.03 (3.65)

As can be seen in Figure 53, participants' speed in the 30 km/h speed condition was significantly lower during pedestrian interaction (M = 27.8 km/h) than before pedestrian interaction (M = 31.3 km/h). On average, participants reduced the vehicle's speed was reduced by approximately 2.8 km/h.

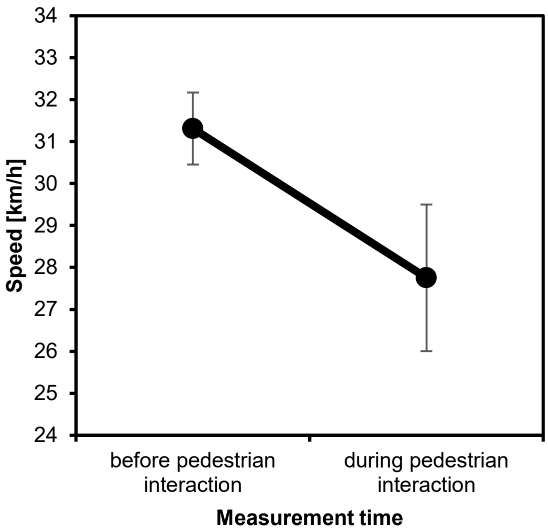
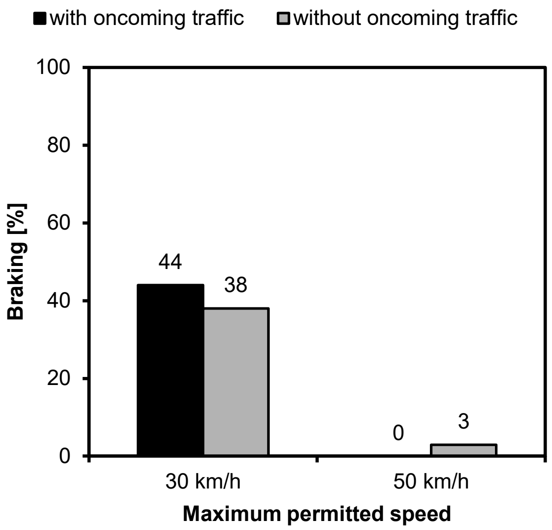


Figure 53 Speed change (means with 95 % CI) depending on the measurement time (T) in the condition with a maximum permitted speed of 30 km/h.

8.3.2.2 Brake reaction

As shown in Figure 54 left, almost half (44 %) of the participants braked in the 30 km/h condition if with oncoming traffic was present and more than a third (38 %) without oncoming traffic. In contrast, only one driver braked in the condition with a maximum permitted speed of 50 km/h. This is in line with the previously reported results on speed change (see Chapter 8.3.2.1). A further analysis of the maximum brake pedal position showed that drivers braked weakly (see Figure 54 right). The maximum brake pedal position ranges between 0 and 9.



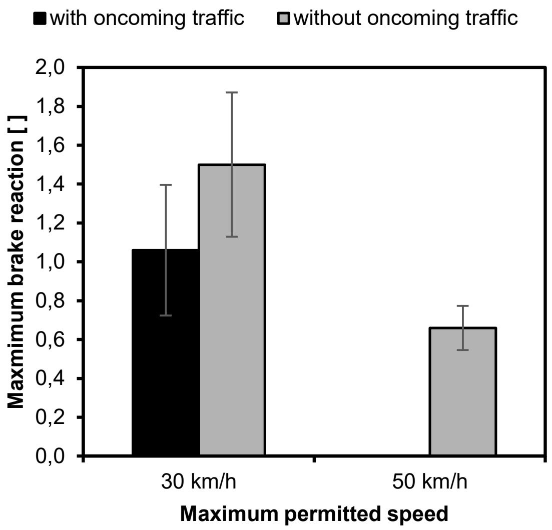


Figure 54 Left: Percentage of participants braking during pedestrian interaction (means with standard deviation) depending maximum permitted speed (S) and oncoming traffic (O). Right: Maximum brake reaction during pedestrian interaction (means with standard deviation) depending on the maximum permitted speed (S) and oncoming traffic (O).

8.3.2.3 Change in lateral offset

The statistical tests performed for the outcome variable change in lateral offset (before vs. during pedestrian interaction) are reported in Table 54, separately for the 30 km/h and 50 km/h conditions. Table 55 provides the mean values and standard deviations for this outcome variable. Regarding the reported mean values, please note that positive mean values represent a lateral deviation from the center of the lane to the right and negative values represent a corresponding lateral deviation from the center of the lane to the left. The analysis revealed significant interaction effects of the factors measurement time and oncoming traffic on the change in lateral offset in the 30 km/h and 50 km/h conditions (see Figure 55). Furthermore, there were significant main effects of measurement time and oncoming traffic on change in lateral offset in the 30 km/h and 50 km/h conditions.

Table 54 Statistical tests (repeated-measures ANOVA) including the within-subjects factors measurement time and oncoming traffic regarding the outcome variable change in lateral offset (before vs. during pedestrian interaction).

		Effect	*F*	*df*	*p*	η^2_{par}
Change in lateral offset	30 km/h	T	7.8	1,31	**.009**	.20
		O	38.0	1,31	**< .001**	.55
		T x O	4.8	1,31	**.036**	.13
	50 km/h	T	10.4	1,31	**.003**	.25
		O	23.2	1,31	**< .001**	.43
		T x O	9.5	1,31	**.004**	.24

Table 55 Mean values and standard deviations including the within-subjects factors measurement time, and oncoming traffic regarding the outcome variable change in the lateral offset (in m).

		Oncoming traffic	
	Maximum permitted speed	yes	no
Lateral offset before pedestrian interaction	30 km/h	0.17 (0.20)	-0.02 (0.23)
	50 km/h	0.08 (0.21)	-0.15 (0.25)
Lateral offset during pedestrian interaction	30 km/h	0.09 (0.21)	-0.27 (0.54)
	50 km/h	0.23 (0.21)	-0.01 (0.19)

In the 30 km/h condition (see Figure 55 left), participants had a slight offset to the right before pedestrian interaction if oncoming traffic was present (M = + 0.17 m) whereas in the condition without oncoming traffic, participants drove in the center of the lane (M = - 0.02 m). As a reaction to the pedestrian, participants drove a lateral offset to the left regardless of the presence of oncoming traffic. However, the lateral offset to the left was larger if there was no oncoming traffic present on the left-hand side (M = - 0.28 m) compared the condition where oncoming traffic was present (M = + 0.09 m). In total, drivers' lateral offset changed by 0.08 m in the condition with oncoming traffic, and by 0.27 m in the condition without oncoming traffic.

In the 50 km/h condition (see Figure 55 right), the vehicle's position remained nearly unchanged during pedestrian interaction compared to before pedestrian interaction, being almost perfectly centered at both measurement times if there was no oncoming traffic present (M_{before} = - 0.02 m; M_{during} = - 0.004 m). However, in the condition with oncoming traffic, drivers drove a lateral offset to the right (M_{before} = + 0.08 m; M_{during} = + 0.23 m). So, the vehicle's lateral offset changed by 0.15 m compared to before pedestrian interaction.

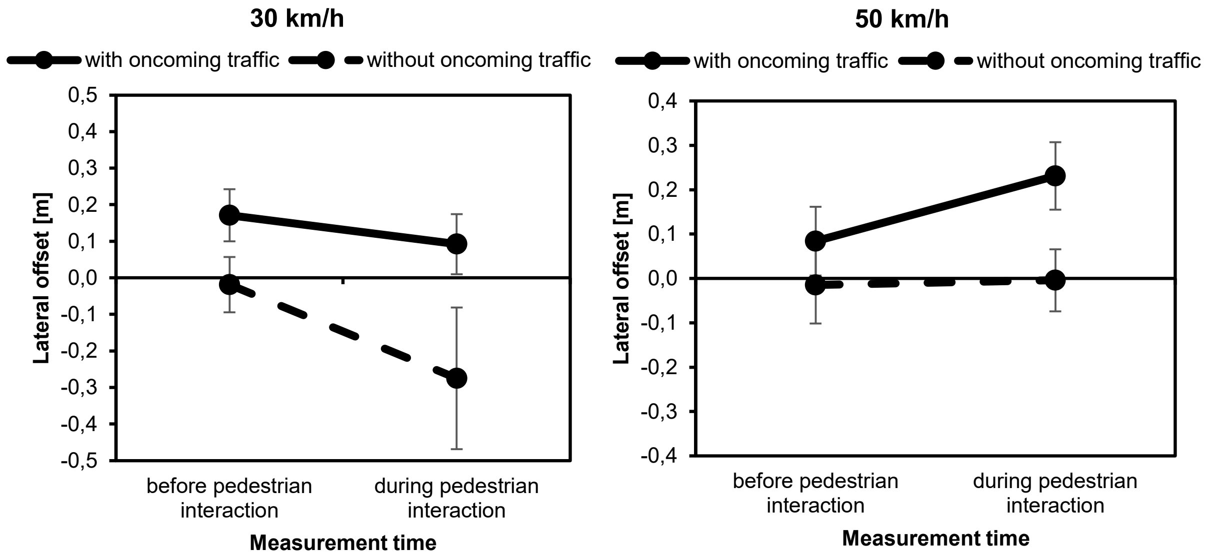


Figure 55 Change in lateral offset (means with 95 % CI) depending on oncoming traffic (O, and the measurement time before and during pedestrian interaction (T). Left: 30 km/h condition. Right: 50 km/h condition.

8.4 Discussion

Study 3 examined passengers' perceived risk and comfort during automated driving in a typical pedestrian interaction in longitudinal urban traffic. In the first part of the study, passengers' perceived risk and comfort were examined depending on pedestrian presence (with / without) in the parking stand on the right-hand side of the road, the presence of oncoming traffic (with / without) and the driving behavior of the highly automated vehicle which included conditions of speed (30 km/h / 50 km/h) and lateral guidance (offset to the left / offset to the right / no offset). In addition, the highly automated vehicle decelerated prior to pedestrian interaction in six selected conditions of the driving scenario. The second part of the study investigated how passengers would *ideally* want to be driven in the highly automated vehicle in the examined driving scenario. To this end, participants completed four selected conditions of the driving scenario manually in a way they considered *ideal* highly automated driving behavior. This was done to verify whether the configurations implemented in the first part were acceptable for passengers. In addition, this procedure allowed the identification of further relevant driving parameters that may be decisive for passengers' perceived risk and comfort, but which were not covered in the first part of the present study. In the following sections, the obtained results are discussed and recommendations for the configuration of a highly automated driving functions are derived.

8.4.1 Passengers' perceived risk and comfort

In the first part of the present study, participants rated perceived risk and comfort after each condition. Across the experimental conditions, perceived risk was rated between the labels *harmless* and *very unpleasant*, but not as *dangerous*, with mean ratings being higher, i.e. more dangerous, in the 50 km/h condition compared to the 30 km/h (see Figure 33). Understandability was rated between average and high, with mean ratings being higher at lower speed (30 km/h) than at higher speed (50 km/h; see Figure 38). At the same time, perceived loss of control was rated low to average, being rated lower at 30 km/h than at 50 km/h (see Figure 35), supporting the results obtained for the understandability and perceived risk ratings. Nevertheless, even at a speed of 50 km/h, driving the maximum permitted speed was still within an acceptable range regarding passengers' perceived risk and driving comfort. So, it can be concluded that driving the maximum permitted speed is acceptable for passengers. In addition, this finding may have a positive side effect on overall traffic flow in mixed traffic, as other drivers would not be slowed down by highly automated vehicles. Thus, highly automated vehicles would not interfere with other human drivers' goals to make progress in traffic, arriving timely at their destination of travel (Summala, 2007). At the same time, highly automated vehicles would also fulfil the social norms in road traffic by displaying similar behavior patterns as human drivers (see Summala, 2007).

Moreover, passengers preferred driving in the center of the lane over the lateral offsets to the left or right, with lateral distances to the oncoming traffic, the pedestrian, and the parked vehicle being rated as almost *ideal* in this condition (see Figure 45; see Figure 47 – Figure 48). However, passengers rated a lateral offset to the left just as safe and understandable as driving without lateral offset if there was no oncoming traffic present. In the survey, 56 % of the passengers stated that a lateral offset to the left would be desirable if a pedestrian was present on the right-hand side, but no oncoming traffic on the left-hand side.

By adjusting its trajectory, the highly automated vehicle “informed” its passenger that it has detected the visually obstructed pedestrian on the right-hand side and, in reaction, maintained a larger distance from the pedestrian to avoid the potential hazard. So, a trajectory adaptation by means of a lateral offset is recommendable in selected conditions of the examined driving scenario. Thus, behavioral adaptations as a form of “implicit HMI” (Hartwich et al., 2020, p. 43) may supplement existing considerations on passenger feedback via internal HMIs (e.g., Feierle et al., 2018; Hartwich et al., 2020; Lau et al., 2020; Wilbrink et al., 2020; see Bengler et al., 2020 for a review), thereby fulfilling its passenger’s individual information needs and improving the understandability and transparency of automated driving behavior (see Beggiato, Hartwich et al., 2015; Hartwich et al., 2020).

However, obtained results also showed that the adaptation of the trajectory must be appropriate to the driving situation. While the lateral offset to the left in the presence of a pedestrian without oncoming traffic was a good way to show the passenger that the automated vehicle adapts its behavior appropriately, the same adaptation proved less acceptable with oncoming traffic. Instead of a lateral offset, a deceleration contributed to passenger comfort effectively by decreasing perceived loss of control in this situation.

These findings provide some backing for Summala’s comfort zone model (2007) and the *Zero Risk Theory* (Näätänen & Summala, 1974, 1976; Summala, 1988) as passengers in the present study aimed to maintain a certain safety margin from a potential hazard. This theory may also explain the finding that a majority of passengers rejected lateral offset to the right, being rated *very unpleasant* on the perceived risk scale and resulting in lower comfort ratings (low understandability ratings, high perceived loss of control ratings). In the survey, more than two thirds (69 %) of the passengers stated that they considered an offset to the right dangerous driving behavior without pedestrian presence. In the condition where a pedestrian was present on the parking stand, over 90 % of the passengers rejected a lateral offset to the right as passengers may want to avoid passing too close to the pedestrian. In addition, the parked vehicle on the right-hand side may have contributed to these ratings as passengers may have wanted to avoid a collision with the parked vehicle as well. In addition, participants may have suspected that a person would suddenly open the driver's door, stepping out of the parked vehicle onto the road without paying attention to traffic. Thus, if the highly automated vehicle would drive a lateral offset to the right in this situation, would possibly signal its passenger that it failed to recognize the potential hazard and / or fails to react appropriately.

At the same time, the behavioral adaptations in the automated vehicle’s trajectory are visible from the outside perspective of vulnerable users in the driving environment. So, the automated vehicle could use its kinematics to communicate to vulnerable road users in the driving environment that it has recognized a potential space-sharing conflict. Previous research has highlighted the importance of kinematic cues for pedestrians and cyclists in interactions with (automated) vehicles in the urban environment (e.g., Ackermann et al., 2019; Beggiato et al., 2018; Fuest et al., 2018, 2019; Lee et al., 2020; Stange et al., submitted). So, behavioral adaptation as a type of implicit communication could supplement existing considerations regarding the external display of intentions by means of eHMIs (see Chapter 3.2).

8.4.2 Passengers’ preferences regarding highly automated driving behavior

The second part of the present study investigated how passengers ideally want to be driven in the examined driving situation when interacting with a pedestrian. To this end, participants were asked to complete in four selected conditions of the driving scenario manually in the way they would ideally like a highly automated vehicle to drive in the respective situation. Regarding this ideal highly automated driving behavior, the aspects of speed, deceleration and the lateral offset were analyzed.

Regarding the speed configuration, the results showed that the speed should be adapted to the respective maximum permitted speed on the given road section (see Table 53). This finding is in line with the results obtained in the first part of the present study. So, it can be concluded that the configuration of speed in the first part had already met with passengers’ preference.

Regarding the aspect of deceleration, passengers preferred a speed reduction by approximately 3 km/h to 4 km/h in the 30 km/h condition whereas passengers preferred no speed reduction in the 50 km/h zone (see Figure 54). Compared to the pre-defined deceleration rates (30 km /h: 20 % reduction to 24 km/h; 50 km/h: 20 % reduction to 40 km/h) in the first part of the study, the reduction of speed was noticeably lower in the second part of the study. In addition, only half of the participants decelerated in the 30 km/h zone and only one participants decelerated in the 50 km/h zone. An explanation for this finding could be that passengers may want to avoid endangering (potential) following drivers who need to react to the preceding highly automated vehicle’s braking maneuver in time. At the same time, deceleration compromises passengers’ goal to make progress (Summala, 2007). Taken together, these findings suggest that deceleration is optional, but not essential in the examined driving situation.

Regarding the lateral offset, the results obtained in the second part of the study indicate that passengers preferred a small lateral offset to the left in the 30 km/h condition if there was no oncoming traffic present (see Figure 55). The size of this lateral offset to the left was smaller (< 0.2 m) compared to the first part of the present study (0.5 m). In the 50 km/h condition, passengers preferred no lateral offset if there was no oncoming traffic present (see Figure 55). However, in the presence of oncoming traffic, passengers drove a slight offset to the right (≈ 0.2 m) in the direction of the pedestrian and the parked vehicle. In the first part of the study, passengers rejected a larger offset to the right (0.5 m), rating this driving behavior as very unpleasant and uncomfortable. So, passenger may have aimed to avoid driving too close to the oncoming traffic as a collision at a higher speed of 50 km/h may cause serious injury. At the same time, neither the parked vehicle, nor pedestrian on the parking stand on the right-hand side were on direct collision course with the highly automated vehicle. Therefore, it could be hypothesized that passengers' perceived driving closer to the parked vehicle and the pedestrian as safer than driving closer to the oncoming traffic.

8.5 Recommendations for automated driving function developers

Overall, the results obtained in the two parts of the present study are consistent. The obtained results from the two study parts showed that passengers prefer a behavioral adaptation of the vehicle's trajectory in the presence of a pedestrian as it lowers perceived risk and enhances passenger comfort. However, there were discrepancies between the two study parts regarding the exact configuration of the behavioral adaptations. Both the size of the lateral offset and the extent of the speed reduction were smaller in the second part of the study than in the first part.

Taking the aspect of oncoming traffic into account, the following behavioral adaptations of highly automated vehicles recommended for the examined driving scenario:

- Without oncoming traffic on the left-hand side, a slight offset to the left should be driven in the presence of a pedestrian on the right-hand side (≈ 0.2 m) at lower speed (30 km/h) whereas at higher speed (50 km/h) the highly automated vehicle should drive in the center of the lane.
- In the presence of oncoming traffic, the highly automated vehicle should drive in the center of the lane, regardless of the driven speed.
- A slight deceleration before pedestrian interaction is recommendable (by approximately 1.0 m/s^2).

8.6 Limitations

Study 3 is subject to a number of limitations. Due to the cooperation with function developers, the implementation of the highly automated driving function was based on well-founded assumptions on the technical capacities and limitations regarding the configuration of the highly automated driving function. Thus, it was possible for passengers to experience an authentic highly automated driving function (Level 4; SAE, 2014, 2018) in the driving simulator. In the context of the present study, however, it was not possible to implement all technically feasible configurations the of the highly automated driving function, taking into account all driving parameters. Instead, selected configurations of two relevant parameters, vehicle speed and lateral offset, were implemented in a realistic driving scenario.

In the examined driving scenario, the pedestrian was not blocking the lane of the highly automated vehicle, so that from the passenger perspective inside the automated vehicle no direct collision with the pedestrian was to be expected. Thus, the lack of a direct collision course in this space-sharing conflict may have contributed to the fact that the subjective ratings of perceived risk were located mainly in the lower half of the scale between the labels *harmless* and *very unpleasant* (see Figure 31). In order to increase the criticality of this potential space-sharing conflict, the pedestrian may step onto the road in order to cross it in front of the highly automated vehicle or the pedestrian may walk toward the parked vehicle, opening the driver's door to enter the parked car which may result in the highly automated vehicle being on a direct collision course with the pedestrian and / or the parked vehicle.

From a methodological perspective, it should also be noted that participants were aware at all times that they were in a safe experimental situation in the driving simulator. This awareness may have contributed to a potential underestimation of passengers' perceived risk and / or to an overestimation of driving comfort in the present study. Therefore, it is possible that participants would evaluate the same technical configurations of highly automated driving behavior differently in the same driving situation in real-world driving.

Moreover, the space-sharing conflict examined in this study was limited to *one* dyadic interaction with *one* vulnerable road user in this specific urban driving scenario. Due to this simplification, passengers' attention was drawn to the comparison of the configurations of highly automated driving behavior in this specific driving scenario. At the same time, however, this approach reduced the proximity to reality, neglecting the complexity of everyday driving in urban road traffic, where sometimes a large number of human road users interact with each other (cyclists, pedestrians, motorists). Therefore, it is necessary to investigate how passengers would want to be driven automatically in more complex driving situations, interacting with several vulnerable road users sequentially or even simultaneously.

Furthermore, participants had no personal experience as passengers inside highly automated vehicles prior to the present study. Consequently, participants may not have formed any preferences regarding the driving style of these vehicles yet. Therefore, it is possible that the task in the second part of the experiment, to drive as one would prefer for a highly automated vehicle in this situation, was very challenging for participants. Although participants had experienced a number of different configurations of a highly automated driving function in the first part of the study, these simulator drives were no adequate substitute for the lack of personal experience. In addition, participants are not used to performing specific driving maneuvers in the driving simulator. Therefore, the results of the second part of the study are to be understood as an approximation to an ideal highly automated driving behavior. To ensure that the driving behavior demonstrated by the drivers in the second part of the present study actually corresponded to their preferred highly automated driving behavior, drivers would have had to experience their own drives in replay as passengers. However, this replay was not done in view of the long duration of the study (120 minutes).

Finally, the present study was conducted in a static driving simulator, so participants had no physical feedback from the simulator in terms of longitudinal and lateral acceleration which is one of the major methodological limitations of driving simulator studies (see Bubb, 2015). At the same time, physical feedback is decisive for passengers' experience of driving comfort (see Bellem et al., 2018; Elbanhawi et al., 2015). Due to this limitation, the driving function is planned to be validated in a real-world driving study using a *Vehicle-in-the-Loop* on a test track (for more background see Bock et al., 2007; Bubb, 2015; Solmaz et al., 2020; Tettamanti et al., 2018).

8.7 Conclusions

Summing up, the study provides evidence that passengers inside the highly automated vehicle perceived the presented configurations as mainly safe, and comfortable. Based on passenger ratings, recommendations for technical development were derived. The adaptation of the trajectory in terms of deceleration and lateral offset is recommended to provide the passenger with direct feedback that the highly automated system has recognized a potential hazard in the driving environment. When adapting the trajectory, this adaptation must be appropriate, i.e. the highly automated system must include the current circumstances and all relevant elements of the driving environment in its behavioral decisions. Due to constraints of the driving simulator environment, the results obtained in the present study are planned to be validated in a follow-up study on a test track using a vehicle-in-the-loop – outside the scope of this dissertation.

9 Study 4 – Approaching an urban junction with crossing pedestrians and cyclists

9.1 Objective and research questions

Following on from Study 3, the present study aimed to further investigate how passengers want to be driven automatically in mixed traffic interactions with vulnerable road users. Specifically, Study 4 focused on the question of when a passenger wants the highly automated vehicle to start braking when approaching an urban junction. Furthermore, passengers' perceived risk was examined in this driving situation.

To this end, a junction with crossing cyclists and pedestrians was implemented in the driving simulator. Passengers inside the highly automated ego-vehicle approached the junction at a speed of 30 km/h or 50 km/h (vehicle speed, between-subjects factor) where a pedestrian or a cyclist (type of vulnerable road user, between-subjects factor) crossed from the left-hand or the right-hand side (vulnerable road user's direction, within-subjects factor). Participants' task was to initiate the vehicle's braking maneuver at the ideal braking onset and the last, acceptable braking onset time (braking onset time, within-subjects factor). Study 4 examined the following research questions:

RQ 1: When should a highly automated vehicle *ideally* start to brake from a passenger's point-of-view, when approaching a junction with crossing vulnerable road users?

RQ 2: When is the last, acceptable braking onset time from a passenger's point-of-view, when approaching a junction with crossing vulnerable road users?

RQ 3: How much perceived risk are passengers willing to accept in the interaction with vulnerable road users at an urban junction?

As the vast majority of human drivers have no experience as passengers in highly automated vehicles yet, it is reasonable to assumed passengers may prefer early braking onset times at first, possibly even earlier than in non-automated driving as they may want to avoid experiencing risk (see Näätänen, & Summala, 1974, 1976; Summala, 1988). However, it is largely unclear how passengers want to be driven automatically in this driving situation, and, how much risk humans would accept (Nolte et al., 2018). Due to the explorative approach pursued in Study 4, no directed hypotheses are presented regarding these research questions.

9.2 Methods

Originally, Study 4 was planned to be conducted in the static driving simulator at the Department of Traffic and Engineering Psychology. Due to the spreading Covid-19 pandemic, however, the study was carried out as an online study using pre-recorded videos from the driving simulator.

9.2.1 Driving scenario

Participants in the highly automated ego-vehicle approached the junction at a speed of 30 km/h or 50 km/h from a side road (lane width: 3.25 m per lane) without lane markings (see Figure 56). Depending on the experimental condition, a pedestrian or a cyclist approached the junction from either the left-hand or the right-hand side (from the passenger's perspective), and crossed the road in front of the highly automated vehicle. Cyclists approached the junction at a constant speed of 12 km/h while pedestrians had a constant speed of 3 km/h.

The driving scenario was chosen because it includes a typical interaction space -sharing conflict with vulnerable road users, which will presumably occur frequently when highly automated driving is introduced in urban traffic.

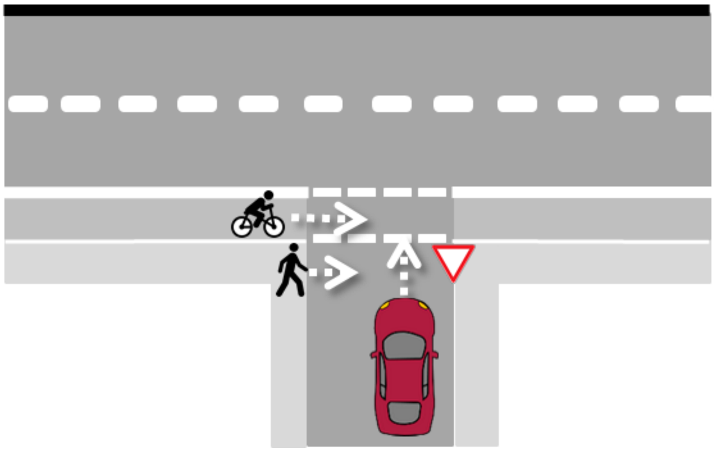


Figure 56 Driving scenario used in Study 4.

The videos were recorded from the passenger's perspective inside the highly automated ego-vehicle approaching the junction (see Figure 57; see Figure 58). The videos started 120 m before the stop line in the 30 km/h condition, and 210 m before the stop line in the 50 km/h condition, so that each video lasted approximately 20 seconds regardless of vehicle speed. In each condition, the highly automated vehicle first accelerated from 0 km/h to the respective target speed, which was reached 125 m in the 50 km/h condition, and 81 m in the 30 km/h condition before the stop line. Passengers were informed about the vehicle's current speed via a head-up display. The distance to the stop line as well as a video number was displayed continuously in the upper left corner of the video.

Figure 57 Driving scenario from the passenger perspective. Left: Cyclist crosses the junction from the left-hand side. Right: Cyclist crosses the junction from the the-right-hand side.

Figure 58 Driving scenario from the passenger perspective. Left: Pedestrian crosses the junction from the left-hand side. Right: Pedestrian crosses the junction from the the-right-hand side.

Before experiencing the driving scenario, participants were given the chance to acquaint themselves with the experimental procedure by means of a training scenario. The training scenario differed from the driving scenario (see Figure 59). In the training scenario, participants in the highly automated ego-vehicle approached the junction at a speed of 40 km/h. The highly automated vehicle came to a halt at the stop line before a stop sign. On the main road, traffic was flowing.

Figure 59 Training scenario from the passenger perspective.

9.2.2 Experimental design

As the present study was conducted as an online study, the duration was intended not to exceed 20 minutes per participant to avoid high drop-out rates. As a consequence, it was not possible to present all experimental conditions to all participants in a repeated-measures design. Instead, the present study followed a 2 x 2 x 2 x 2 mixed design (see Figure 60).

Participants were randomly assigned to one of four experimental groups: (1) cyclist, 30 km/h; (2) cyclist, 50 km/h; (3) pedestrian, 30 km/h; (4) pedestrian, 50 km/h. So, participants inside the highly automated vehicle approached the junction at a speed of either 30 km/h or 50 km/h (vehicle speed, between-subjects factor), and interacted with either a cyclist or a pedestrian (type of vulnerable road user, between-subjects factor).

Within each experimental group, participants experienced two experimental conditions. Once, the cyclist or pedestrian approached the junction from the left-hand, and once from the right-hand side (vulnerable road user's direction, within-subjects factor). In each experimental condition, participants' task was to first initiate the braking onset at the ideal onset time, and then the last, acceptable onset time (braking onset time, within-subjects factor). In total, each participant experienced two experimental conditions including two interactions each (= four interactions per participant).

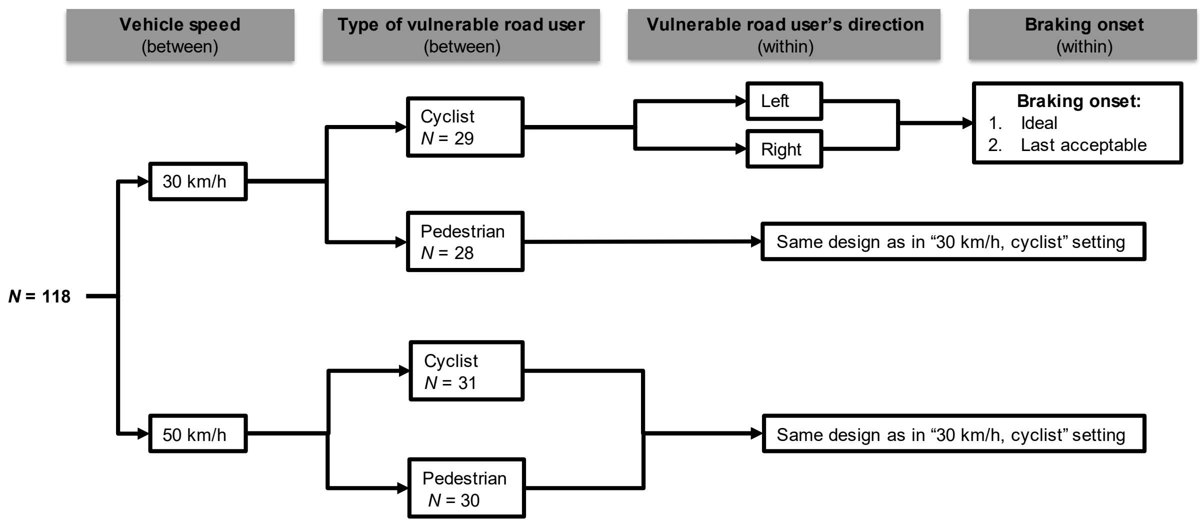


Figure 60 Experimental design and number of participants in each experimental group.

9.2.3 Dependent variables

After each interaction, participants rated perceived risk on the 8-point scale applied in the previous studies (see Figure 6). The four categories (*harmless, unpleasant, dangerous,* *situation not acceptable*) were instructed as in the previous Study 3 (see Chapter 8.2.3). In addition, the distance to the stop line (in m) was recorded for the ideal and the last, acceptable braking onset times. Based on the distance, the time headway to the stop line was calculated for the ideal and the last, acceptable braking onset times.

9.2.4 Procedure

The online study was programmed using the online questionnaire software Unipark (Questback, 2020; https://www.unipark.com/). First, participants were acquainted with the study objective and the experimental procedure, and gave their informed consent for the scientific use of their data. Participants were then given the chance to acquaint themselves with the experimental procedure by means of a training scenario including two trials, (1) ideal braking onset time, (2) last, acceptable braking onset time.

In the first training trial, participants' task was to stop the *test video* at the point in time when the highly automated vehicle should *ideally* start to brake (= ideal braking onset time). When stopping the video, participants were first asked to enter the distance of the vehicle to the stop line in the online questionnaire as displayed in the upper left corner of the video (see Figure 57). In total, eight test videos were pre-produced to cover each experimental condition, using the same test video for the two braking onset times.

Based on the distance to the stop line participants then selected a *check video* (1 – 12) whose number was also displayed in the upper left corner of the test video. Based on the selected video number participants were then shown the selected check video replaying their self-selected ideal braking onset time. For example, if a participant stopped the test video 60 m before the stop line, the participant entered "60" in the online questionnaire, and was shown check video 4. This was done to verify whether the selected braking onset was really participants' ideal braking onset time. For this purpose, twelve check videos were pre-produced for each of the eight experimental conditions using the same check videos for the two braking onset times, plus the training scenario (= 12 x 9 pre-produced check videos in Study 4). The videos included all features of the given experimental condition as specified by the experimental design (see Figure 60).

So, there was a unique set of pre-produced check videos for each experimental condition. Each video covered a certain range of distance to the stop line from the point in time when the vehicle had reached the target speed until the vehicle reached the stop line (30 km/h: - 81 m – 0 m distance to the stop line in steps of 6 m; 50 km/h: - 135 m – 0 m distance to the stop line in steps of 10 m; see Table 56). So, all selected braking onsets falling within the same range resulted in the same check video being shown for replay. Therefore, the check videos may have had some (minimal) deviation of maximum 6 m or 10 m from participants' self-selected braking onset times.

Table 56 Distance to the stop line (in m) at braking onset covered by the pre-produced check videos.

Video number	30 km/h	50 km/h
1	81 - 75	135 - 125
2	75 - 69	125 - 115
3	69 - 63	115 - 105
4	63 - 57	105 - 95
5	57 - 51	95 - 85
6	51 - 45	85 - 75
7	45 - 39	75 - 65
8	39 - 33	65 - 55
9	33 - 27	55 - 45
10	27 - 21	45 - 35
11	21 - 15	35 - 25
12	15 - stop line	25 - stop line

After watching the check video, participants could either correct or confirm their self-selected configuration. In case of a correction, participants re-watched the test video to re-select the braking onset time. In case of a confirmation (or after the correction), participants were asked to rated perceived risk (see Figure 61 for a summary of the experimental procedure).

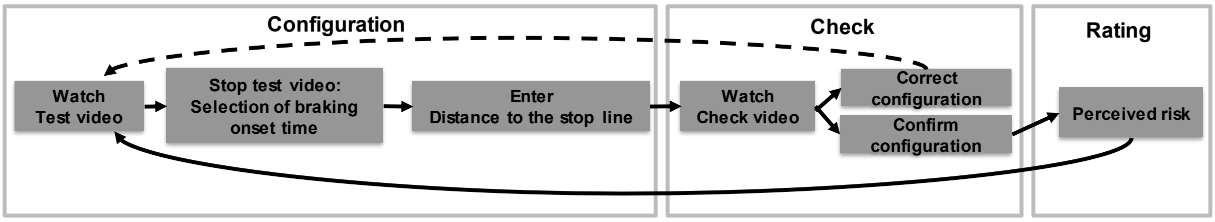


Figure 61 Experimental procedure in each trial.

In the second training trial, participants were asked to stop the test video to mark the last, acceptable point in time they considered safe enough to start braking. Again, participants entered the distance to the stop line as displayed in the upper left corner of the test video in the online questionnaire, watched the corresponding check video, and were given the chance to either correct or confirm their configuration before rating perceived risk of the previous interaction.

Subsequently, participants were randomly assigned to one of the four experimental groups according to the experimental design (see Figure 60). Each participant experienced two experimental conditions including four interactions with either a cyclist or a pedestrian approaching the junction from the left-hand and the right-hand side. The experimental procedure in the test trials was identical to the training scenario. Participants were first asked to stop the video at the ideal braking onset time, and provide a subjective rating of perceived risk. In the second step, participants selected the last, acceptable braking onset time, and, again, rated perceived risk.

After having experienced the last interaction, participants completed a sociodemographic questionnaire including questions on their mobility behavior, technical affinity, and experience with driving assistance systems. After completing the study, participants could take part in a lottery where they could win one of 25 Amazon vouchers worth 10 EURO each. Undergraduate Psychology students at Technische Universität Braunschweig could choose between participation in the lottery or course credit. Finally, all participants were thanked for their participation in Study 4.

9.2.5 Participants

N = 122 participants completed the online study. Datasets of *n* = 4 participants had to be discarded due to missing sociodemographic data. So, the final sample consisted of *n* = 118 participants aged 18 to 75 years (*M* = 36.8 years, *SD* = 16.7 years, 56 female). On average, participants had held their driving license for 18.6 years (*SD* = 16.3 years). Approximately half of the sample (52 %) had an annual mileage of more than 9000 km. Participants' technical affinity was above average (*M* = 4.06, *SD* = 1.07) on the 6-point ATI scale (Affinity for Technology Scale; Franke et al., 2019). The majority (75 %) of participants reported that previous experience with driving assistance systems whereof 25 % reported experience with an emergency braking assistance system. 50 % of participants reported that handing over control of the driving task to an automated system would be rather uncomfortable or very uncomfortable for them whereas 27 % of the participants stated handing over control would be rather comfortable or very comfortable.

Data collection took place from June 2020 to August 2020. Participants were recruited from an internal database, via social media and a press release to create a heterogeneous sample. The only prerequisite for participation was a valid driving license. The study took approximately 20 to 30 minutes to complete per participant, depending on the number of braking onset time corrections. The study was approved by the ethics committee of Faculty of Life Sciences at Technische Universität Braunschweig.

9.2.6 Data analysis

Due to the nested structure of the experimental design, linear mixed models including the between-subjects factors type of vulnerable road user and vehicle speed as well as the within-subjects factors vulnerable road user's direction and braking onset time were fitted to analyze passengers' perceived risk ratings, the distance to the stop line (at braking onset), and the time headway to the stop line (at braking onset).

In each model, all analyzed factors were treated as fixed effects, and all possible main and interaction effects were included in the models. Estimations were based on restricted maximum likelihood (REML). Unstructured variance was chosen as the repeated covariance type. All means reported in Study 4 are presented with 95% confidence intervals (CI). A significance level of $p \leq .05$ was used for all statistical tests. In regard of the exploratory approach of the study, alpha was not adjusted in order to better detect relevant effects while at the same time minimizing interpreting random variations. IBM SPSS Statistics Version 25 was used for statistical data analysis.

9.3 Results

9.3.1 Perceived risk

Table 57 shows the mean values and standard deviations as well as the number of participants in each experimental group for the outcome variable perceived risk. To give an impression of the distribution of perceived risk ratings, the empirical distribution of the ratings in the sample depending on speed (30 km/h, 50 km/h) and braking onset time (ideal onset time; last, acceptable onset time) is visualized in Figure 62.

Table 57 Mean values, standard deviations, and number of participants in each experimental group for the outcome variable perceived risk.

			Braking onset time	
Vehicle speed	Type of vulnerable road user	Direction	Ideal	Last
30 km/h	Cyclist	Left	1.61 (1.10) *n* = 28	2.64 (1.62) *n* = 28
		Right	1.75 (1.14) *n* = 28	2.71 (1.78) *n* = 28
	Pedestrian	Left	1.52 (0.93) *n* = 31	3.29 (1.97) *n* = 31
		Right	1.55 (0.93) *n* = 31	3.35 (1.89) *n* = 31
50 km/h	Cyclist	Left	1.86 (1.13) *n* = 29	3.48 (1.60) *n* = 29
		Right	1.90 (1.11) *n* = 29	3.24 (1.68) *n* = 29
	Pedestrian	Left	1.77 (1.17) *n* = 30	3.37 (1.63) *n* = 30
		Right	1.73 (1.02) *n* = 30	3.10 (1.54) *n* = 30

As can be seen in Figure 62, the vast majority of the perceived risk ratings were located in the lower half of the perceived risk scale (30 km/h: 98 %, 50 km/h: 96 %), with risk ratings ranging between the labels *harmless*, and *very unpleasant* at the ideal braking onset time. Within this range, most interactions were rated as either *harmless* (30 km/h: 64 %, 50 km/h: 49 %) or *a little unpleasant* whereas only 2 % (30 km/h) to 5 % (50 km/h) of the ratings were rated as *a little dangerous*. Overall, passengers rated the interactions with vulnerable road users as mostly *harmless* or *unpleasant* at maximum, but not as dangerous at the ideal braking onset time. Furthermore, the distribution of risk ratings was largely independent of the driven speed, except for the category *harmless.*

Regarding the last, acceptable braking onset time, 78 % of the ratings were again located within the lower half of the scale in each of the two speed conditions. Within this lower half the scale, the distributions of risk ratings were speed-dependent, with interactions being rated more unpleasant in the 50 km/h condition than those in the 30 km/h condition in the categories *harmless* (30 km/h: 25 %, 50 km/h: 12 %) and *a little unpleasant* (30 km/h: 51 %, 50 km/h: 32 %). For all other categories, ratings of perceived risk were independent of the driven speed. As expected, the percentage of interactions being rated as dangerous was higher compared to the ideal braking onset time. Approximately 22 % of all interactions were rated as *dangerous*, with 10 % being rated *a little dangerous*, and 8 % being rated *medium dangerous*. Only 4 % were rated as *very dangerous*. So, most interactions were rated as unpleasant at maximum. At the same time, some passengers accepted dangerous interactions at the last, acceptable braking onset time.

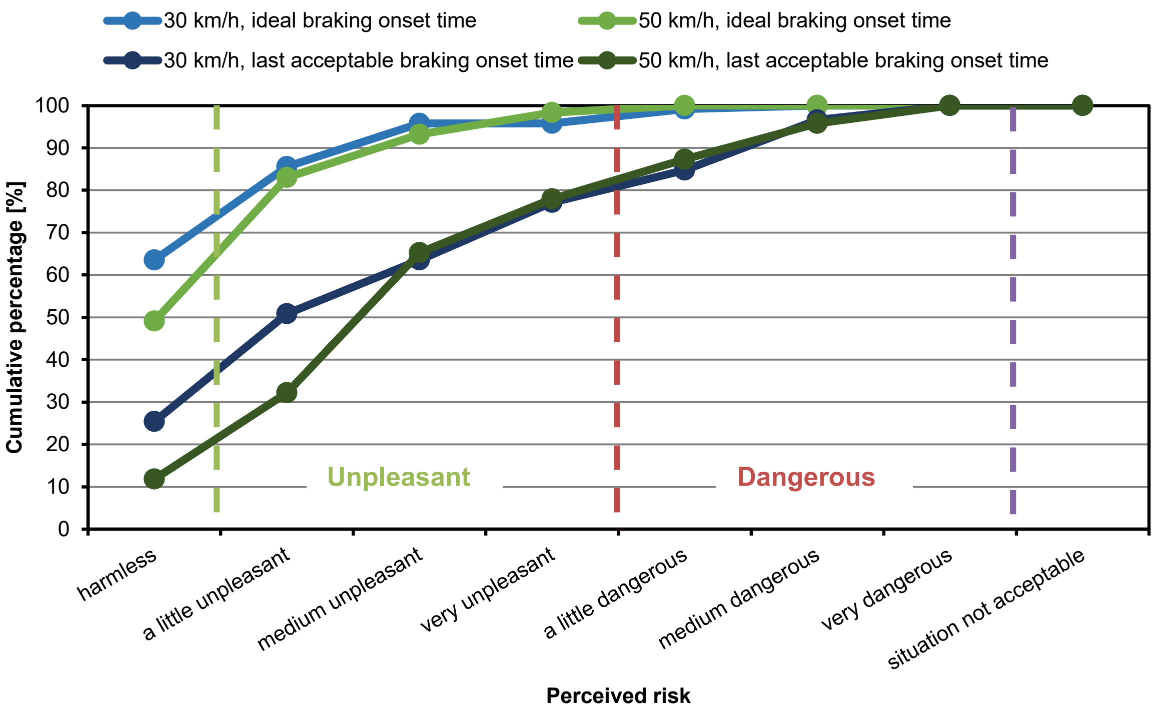


Figure 62 Empirical distribution of perceived risk ratings depending on vehicle speed (S), and braking onset time (B) collapsed across the type of vulnerable road user (T) and the direction (D).

The results of the linear-mixed model calculated for the outcome variable perceived risk are reported in Table 58. The linear mixed model revealed a significant main effect of the within-subjects factor braking onset time on the perceived risk ratings (see Figure 63).

Table 58 Statistical tests (linear mixed model) including all four factors regarding the outcome variable perceived risk (significant p-values in bold).

	F	*df*	*p*
Braking onset time (B)	103.50	1,111.9	**< .001**
Type of vulnerable road user (T)	0.09	1,111.4	.771
Vulnerable road user's direction (D)	0.12	1,88.8	.726
Vehicle speed (S)	1.51	1,111.4	.221
B x T	1.95	1,111.9	.165
B x D	2.11	1,88.8	.149
B x S	0.10	1,111.4	.757
T x D	0.14	1,88.8	.706
T x S	0.84	1,103.7	.361
D x S	2.16	1,88.8	.145
B x T x D	0.15	1,103.7	.699
B x T x S	1.95	1,111.9	.166
B x D x S	1.55	1,103.7	.216
T x D x S	0.01	1,88.8	.965
B x D x S x T	0.03	1,103.7	.872

In line with the empirical distribution of the perceived risk ratings (see Figure 62), passengers rated perceived risk of the self-selected braking maneuver (see Figure 63) significantly higher at the last, acceptable braking onset time (M = 3.15) compared to the ideal braking onset time (M = 1.71). At the ideal braking onset time, passengers' perceived risk ratings ranged between the labels *harmless* and *a little unpleasant* whereas at the last, acceptable braking onset time passengers' perceived risk ratings approximately equaled to the label *medium unpleasant*.

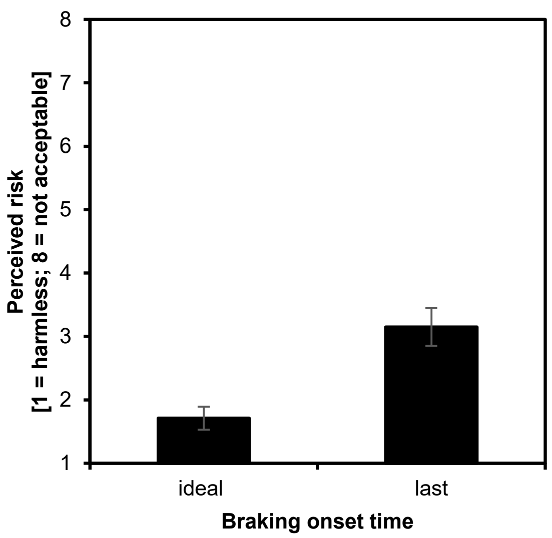


Figure 63 Perceived risk (means with 95 % CI) depending on the braking onset time (B).

9.3.2 Distance to the stop line

Table 59 shows the mean values and standard deviations as well as the number of participants in each group for the outcome variable distance to the stop line. The empirical distribution of the distance to the stop line depending on braking onset time (ideal onset time; last, acceptable onset time) is illustrated for the two vehicle speeds (30 km/h, 50 km/h) in Figure 64.

Table 59 Mean values, standard deviations, and number of participants in each experimental group for the outcome variable distance to the stop line (in meters).

Vehicle speed	Type of vulnerable road user	Direction	Braking onset time	
			Ideal	Last
30 km/h	Cyclist	Left	30.29 (15.37) *n* = 28	22.29 (12.59) *n* = 28
		Right	31.07 (15.15) *n* = 28	23.39 (13.41) *n* = 28
	Pedestrian	Left	31.06 (16.74) *n* = 31	21.26 (13.09) *n* = 31
		Right	31.26 (15.61) *n* = 31	19.97 (10.97) *n* = 31
50 km/h	Cyclist	Left	50.38 (24.13) *n* = 29	34.03 (21.99) *n* = 29
		Right	50.97 (27.19) *n* = 29	37.07 (26.29) *n* = 29
	Pedestrian	Left	57.07 (24.38) *n* = 30	38.30 (19.26) *n* = 30
		Right	54.63 (23.35) *n* = 30	36.37 (15.74) *n* = 30

As expected, passengers' ideal braking onset time was earlier, i.e. in a greater distance from the stop line, than the last braking onset time regardless of the driven speed (see Figure 64). In the 30 km/h condition (see Figure 64 left), 80 % of the passengers (10 % to 90 % quantile) triggered the vehicle's braking maneuver between 54 m and 12 m distance before the stop line marking the deal braking onset time, and between 36 m and 9 m distance to the stop line marking the last, acceptable braking onset time. In the 50 km/h condition (see Figure 64 right), 80 % of the passengers (10 % to 90 % quantile) triggered the braking maneuver between 81 m and 22 m distance before the stop line marking the ideal braking onset time, and between 62 m and 16 m before the stop line marking the last, acceptable braking onset time.

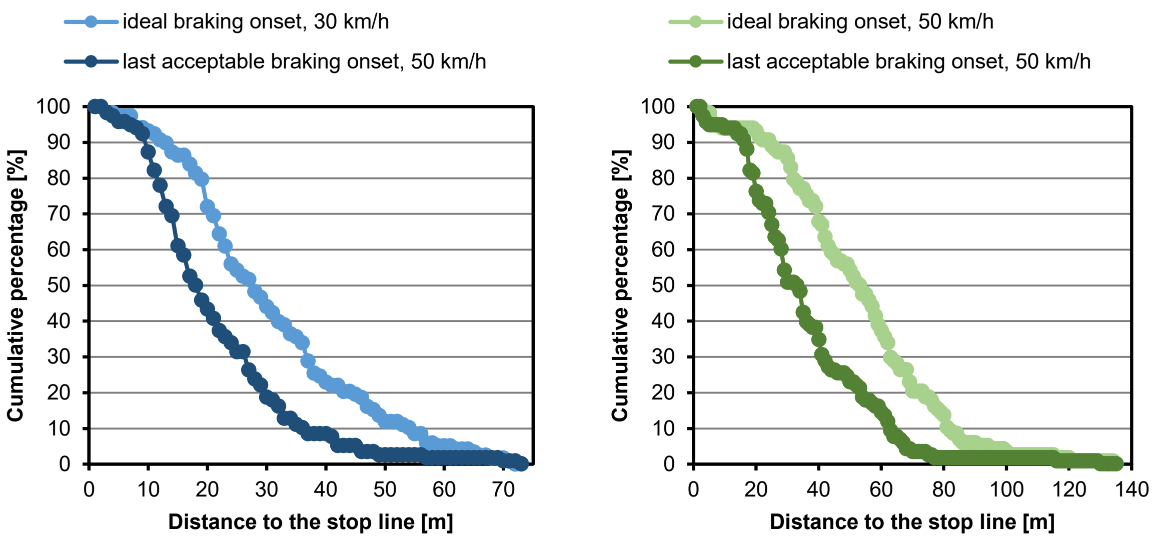


Figure 64 Empirical distribution of distance to the stop line depending on braking onset time (B) for 30 km/h collapsed across the type of vulnerable road user (T) and the direction (D) for 30 km/h (left) and 50 km/h (right).

The results of the linear-mixed model calculated for the outcome variable distance to the stop line is reported in Table 60. The linear mixed model revealed a significant interaction effect between the within-subjects factors braking onset time and vehicle speed (see Figure 65 left), as well as between the between-subjects factor type of vulnerable road user and the within-subjects factor vulnerable road user's crossing direction on the distance to the stop line (see Figure 65 right). Furthermore, there were two significant main effects of the within-subjects factor braking onset time and the between-subjects factor vehicle speed on the distance to the stop line present in the analysis.

Table 60 Statistical tests (linear mixed model) including all four factors regarding the outcome variable distance to the stop line (significant p-values in bold).

	F	*df*	*p*
Braking onset time (B)	234.6	1,92.2	**< .001**
Type of vulnerable road user (T)	0.15	1,91.4	.698
Vulnerable road user's direction (D)	0.00	1,92.2	.992
Vehicle speed (S)	30.64	1,79.1	**< .001**
B x T	3.23	1,91.4	.076
B x D	0.29	1,94.8	.589
B x S	20.16	1,92.2	**< .001**
T x D	4.89	1,79.1	**.030**
T x S	0.42	1,91.4	.517
D x S	0.10	1,79.1	.757
B x T x D	1.30	1,94.8	.258
B x T x S	0.04	1,92.2	.840
B x D x S	1.55	1,94.8	.216
T x D x S	1.01	1,79.1	.317
B x T x D x S	0.00	1,94.8	.966

As can be seen in Figure 65 left, passengers stopped the video significantly earlier, i.e. in a greater distance from the stop line, to mark the ideal braking onset time (*M* = 42.1 m) compared to marking the last, acceptable braking onset (*M* = 29.1 m). Furthermore, the distance to the stop line was significantly greater in the condition with 50 km/h (*M* = 44.9 m) compared to the condition with 30 km/h (*M* = 26.3 m). In addition to these two main effects of the braking onset time and vehicle speed, there was a significant interaction effect between these two factors. In the 50 km/h condition, the difference between the ideal braking onset and the last acceptable braking onset was as high as 17 m whereas the difference between these two braking onsets was only 9 m in the 30 km/h condition.

Figure 65 right shows the interaction effect between the factors type of vulnerable road user and vulnerable road user's direction. If the vulnerable road user approached the junction from the right-hand side, passengers triggered the highly automated vehicle's braking maneuver, on average, 35.6 m before the stop line regardless of the type of vulnerable road user crossing the junction. However, if a vulnerable road user approached the junction from the left-hand side, passengers triggered the highly automated vehicle's braking maneuver significantly earlier, i.e. in a greater distance to the stop line, for a pedestrian (*M* = 36.9 m), and respectively later for a cyclist (*M* = 34.2 m). Despite the statistical significance of this interaction effect, the numerical difference between the distances to the stop line was small, with less than 3 m difference between the four conditions. A similar interaction effect also emerged for the time headway to the stop line (see Figure 67).

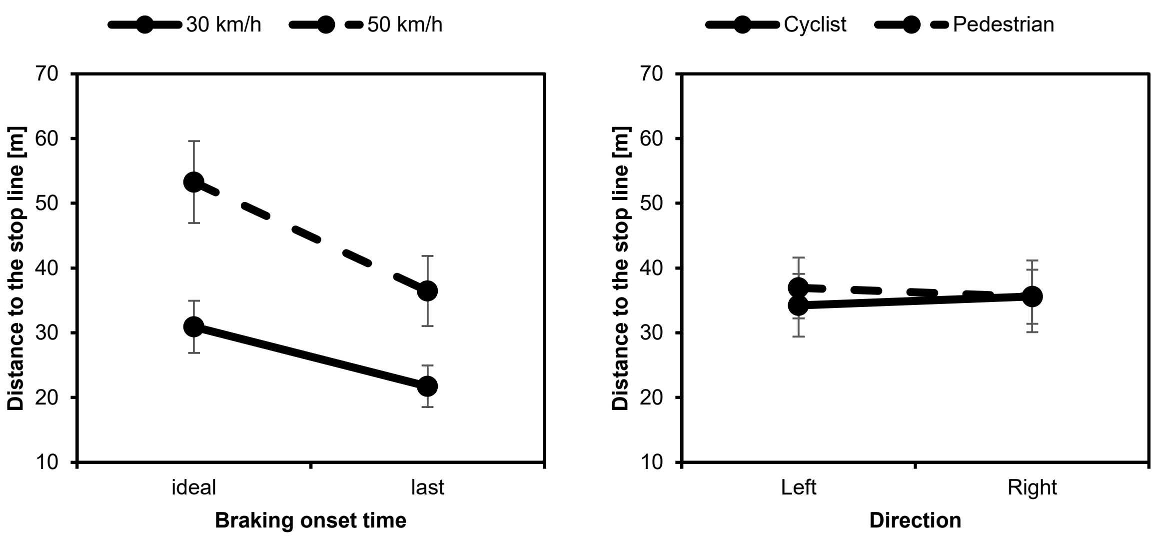


Figure 65 Left: Distance to the stop line (means with 95 % CI) depending the braking onset time (B), and vehicle speed (S). Right: Distance to the stop line (means with 95 % CI) depending on the type of vulnerable road user (T), and the vulnerable road user's direction (D).

9.3.3 Time headway to the stop line

As the highly automated vehicle needed more time and a greater distance to stop when approaching the junction faster, the distances to the stop line were transformed into time headways (distance divided by speed; see Vogel, 2003). This was done to examine the timing of the braking onset regardless of the driven speed (30 km/h, 50 km/h) in the experimental conditions. Table 61 shows the mean values and standard deviations for this outcome variable. Figure 66 visualizes the empirical distribution depending on speed (30 km/h, 50 km/h) and braking onset time (ideal onset; last, acceptable onset).

Table 61 Mean values, standard deviations, and number of participants in each experimental group for the outcome variable time headway to the stop line (in seconds).

Vehicle speed	Type of vulnerable road user	Direction	Braking onset time	
			Ideal	Last
30 km/h	Cyclist	Left	3.63 (1.84) *n* = 28	2.67 (1.51) *n* = 28
		Right	3.73 (1.82) *n* = 28	2.81 (1.61) *n* = 28
	Pedestrian	Left	3.73 (2.01) *n* = 31	2.55 (1.57) *n* = 31
		Right	3.75 (1.87) *n* = 31	2.40 (1.32) *n* = 31
50 km/h	Cyclist	Left	3.63 (1.74) *n* = 29	2.45 (1.58) *n* = 29
		Right	3.67 (1.96) *n* = 29	2.67 (1.89) *n* = 29
	Pedestrian	Left	4.11 (1.75) *n* = 30	2.76 (1.39) *n* = 30
		Right	3.93 (1.68) *n* = 30	2.62 (1.13) *n* = 30

The empirical distributions of the time headway to the stop line show similar patterns as the previously reported distributions of the distances to the stop line (see Figure 66). In the 30 km/h condition (see Figure 66 left), 80 % of the passengers (10 % to 90 % quantile) triggered the vehicle's braking between 6.5 s and 1.4 s time headway before the stop line marking the ideal braking onset time, and between 4.3 s and 1.1 s time headway before the stop line marking the last, acceptable braking onset time.

As expected, passengers wanted the vehicle to brake earlier in the 50 km/h condition compared to the 30 km/h condition (see Figure 66 right). 80 % of the passengers (10 % to 90 % quantile) triggered the braking maneuver between 5.8 s and 1.7 s time headway before the stop line marking the ideal braking onset time, and between 4.5 s and 1.2 s time headway before the stop line marking the last braking onset time.

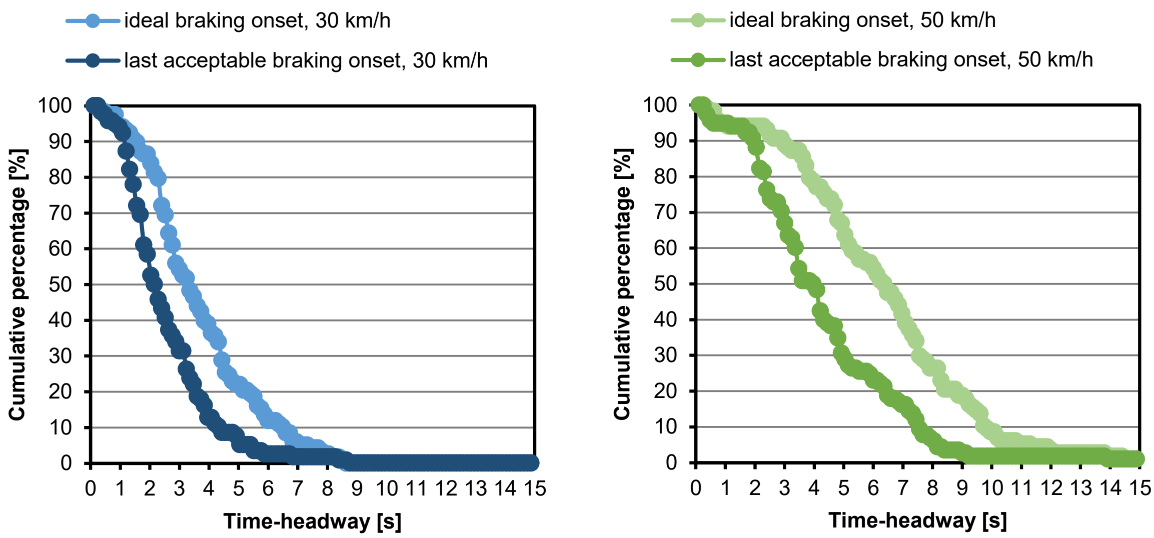


Figure 66 Left: Empirical distribution of time headway to the stop line depending on braking onset time (B) for 30 km/h collapsed across the type of vulnerable road user (T) and the direction (D) for 30 km/h (left) and 50 km/h (right).

The results of the linear-mixed model calculated for the outcome variable time headway to the stop line is reported in Table 62. The linear mixed models each revealed a significant interaction effect between the between-subjects factor type of vulnerable road user and the within-subjects factor vulnerable road user's direction (see Figure 67) as well as a significant main effect of the within-subjects factor braking onset time on the time headway to the stop line (see Figure 68). No further significant main effects or interaction effects were found in the analysis. In contrast to the analysis of the distance to the stop line (see Table 60), no significant main effect of vehicle speed was found, indicating that participants chose the timing of the braking onset taking the highly automated vehicle's speed into account. Similarly, the significant interaction between braking onset and speed found in the analysis of the distance, was not found in the analysis of time headway to the stop line.

Table 62 Statistical tests (linear mixed model) including all four factors regarding the outcome variable time headway to the stop line (significant p-values in bold).

	F	*df*	*p*
Braking onset time (B)	243.03	1,112.3	**< .001**
Type of vulnerable road user (T)	0.06	1,110.7	.805
Vulnerable road user's direction (D)	0.01	1,104.4	.918
Vehicle speed (S)	0.06	1,110.7	.811
B x T	3.68	1,112.3	.058
B x D	0.06	1,113.8	.802
B x S	0.53	1,112.3	.470
T x D	5.25	1,104.4	**.024**
T x S	0.36	1,110.7	.548
D x S	0.13	1,104.4	.715
B x T x D	1.52	1,113.8	.221
B x T x S	0.07	1,112.6	.787
B x D x S	1.47	1,113.8	.227
T x D x S	0.28	1,104.4	.597
B x T x D x S	0.07	1,113.8	.793

As in the analysis of the distances, there was a significant interaction between the between-subjects factor type of vulnerable road user and the within-subjects factor vulnerable road user's direction on the time headway to the stop line (see Figure 67). If the vulnerable road user approached the junction from the right-hand side, passengers triggered the highly automated vehicle's braking maneuver, on average, 3.2 s time headway before the stop line, regardless of the type of vulnerable road user (pedestrian or cyclist). However, if a vulnerable road user approached the junction from the left-hand side, passengers triggered the highly automated vehicle's braking maneuver earlier if the vulnerable road users approaching the junction was a pedestrian (M = 3.3 s), and respectively later for cyclists (M = 3.1 s). Despite the statistical significance of this interaction effect, the numerical difference between the time headways was small, with a difference of less than 0.2 s between the conditions.

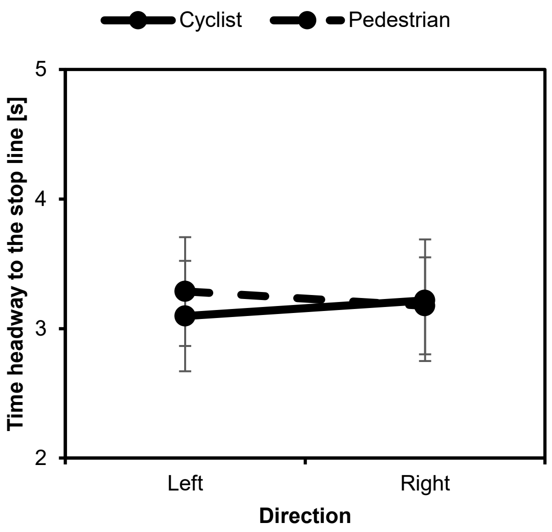


Figure 67 Time headway to the stop line (means with 95 % CI) depending on the type of vulnerable road user (T), and vulnerable road user's direction (D).

As expected (see Figure 68), passengers stopped the video significantly earlier to mark the ideal braking onset time (*M* = 3.8 s time headway before the stop line) compared to marking the last, acceptable braking onset (*M* = 2.6 s time headway before the stop line).

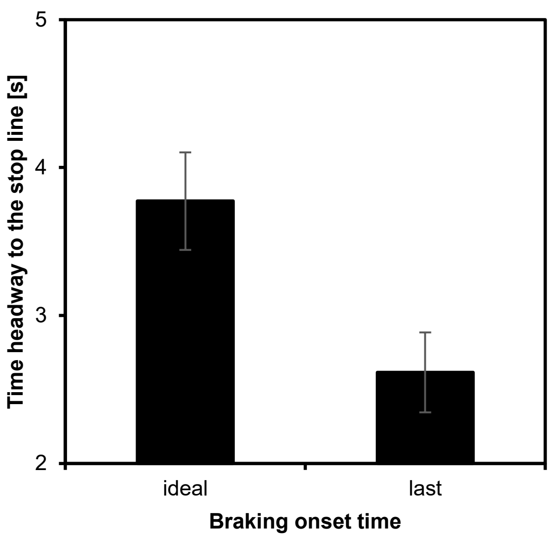


Figure 68 Time headway to the stop line (means with 95 % CI) depending on braking onset time (B).

9.4 Discussion

Study 4 examined from a passenger's perspective how a highly automated vehicle should operate when approaching a junction with crossing vulnerable road users. Specifically, the present study explored when passengers want the highly automated vehicles to start braking, which was measured by means of the distance (in meters) and time headway (in seconds) to the stop line at the ideal and the last, accepted braking onset time. To this end, an urban junction with crossing cyclists and pedestrians was implemented in the driving simulator. In this driving scenario, the speed of the highly automated vehicle approaching the junction (30 km/h, 50 km/h), the type of vulnerable road user (pedestrian, cyclist) and the crossing direction (left, right) of the vulnerable road user were varied. Due to the Covid-19 pandemic, Study 4 was conducted as an online study including pre-produced videos, each lasting approximately 20 seconds. Participants' task was to stop the video to trigger the highly automated vehicles braking maneuver at the distance to the stop line at the point in time they considered the ideal braking onset time and at the point in time they considered the last accepted braking onset time. Participants then watched a check video replaying their self-selected braking onset time. Based on this check video, participants could either confirm or correct their self-selected configuration once. After the final confirmation, participants rated perceived risk for the previous interaction.

9.4.1 Ideal and last, acceptable braking onset timing from a passenger's perspective

In each interaction with a vulnerable road user, passengers triggered the highly automated vehicle's braking onset time by stopping the test video. As the empirical distributions of the distance (see Figure 64) and the time headway (see Figure 66) to the stop line show, passengers' preference of when the highly automated vehicle should start to brake while approaching the junction is highly individual, and as expected, speed-dependent.

In the 30 km/h condition, passengers wanted the highly automated vehicle to ideally start braking 31 m (3.7 s time headway) before the stop line, and at the latest 21 m (2.6 s time headway) before the stop line. In the 50 km/h condition, passengers wanted the highly automated vehicle to ideally start braking 51 m (3.8 s time headway) before the stop line, and at the latest 31 m (2.6 s time headway) before the stop line. These obtained mean distances to the stop line allow for comfortable, smooth braking maneuvers as the following calculations of the braking distance illustrate:

Approaching the junction at a speed of 50 km/h, the highly automated vehicle needs approximately 48 m to come to a halt at deceleration rate of 2.0 m/s^2, provided the deceleration rate was uniform. The braking distance is 3 m smaller than the average distance to the stop line at the ideal braking onset time, so this is, in theory, a safe maneuver. At the last, acceptable braking onset time, the highly automated vehicle's deceleration rate should be at least 3.12 m/s^2 (≈ 31 m braking distance) in order to come to a halt before the stop line. This is still far from an emergency braking maneuver with deceleration rates ranging typically up to approximately 9 m/s^2.

Approaching the junction at a speed of 30 km/h, the highly automated vehicle needs approximately 17 m to come to a halt at deceleration rate of 2.0 m/s^2. The braking distance is 13 m smaller than the average distance to the stop line at the ideal braking onset. This again, would be a comfortable braking maneuver. At the last, acceptable braking onset, the highly automated vehicle's deceleration rate should be at least 1.7 m/s^2 (≈ 21 m braking distance) in order to come to a halt before the stop line. As the automated vehicle is driverless, the driver's reaction time was neglected in these calculations.

However, it should be noted that braking maneuvers are never uniform (see Gratzer, 2007), and the deceleration rate depends on a number of parameters including the vehicle type, tire equipment, road condition and tire/road friction (for an overview see Gratzer, 2007). So, the presented calculation is an approximation to the braking distance in real-world driving, serving the purpose to give an impression of the practical implication of the obtained mean distances and time headways to the stop line.

Summarizing the obtained results, passengers want an early feedback from the highly automated system to confirm that the system has detected the vulnerable road user crossing the junction, and to brake early to maintain a large safety margin to the vulnerable road users as moving obstacles (see Summala, 2007). These findings are consistent with findings from the previous Study 3 (see Chapter 8.4.1). Interestingly, passengers' preference for an early feedback was largely independent of the type of vulnerable road user and the crossing direction, with time headways being very similar for the two examined vehicle speeds. So, it is reasonable to assume that passengers make no difference between slower-moving pedestrians and faster-moving cyclists or the infrastructural features, for example, uni-directional or bi-directional bicycle lanes. Instead, passengers aim to avoid any collision with any vulnerable road user.

From the external perspective of vulnerable road users, previous research on pedestrian interactions with automated vehicles showed that pedestrians want to ensure the automated vehicle has detected them before crossing in front of the vehicle (e.g., Rothenbücher et al., 2016; Lundgren et al., 2017). So, an automated vehicle's early braking reaction can be clear implicit communication signal to vulnerable road users that it is safe to cross, which is a positive side effect of this study and in line with previous research (see Fuest et al., 2018; 2019). A pedestrian simulator study using virtual reality by Dietrich et al. (2020) showed that pedestrians benefit from an automated vehicle's defensive deceleration strategy in a crossing situation.

At the same time, it is also conceivable that passengers want the automated system to convey a feeling of safety to vulnerable road users as passengers may want to be driven in an automated vehicle with a "friendly" driving style, being evaluated positively by other human road users in the driving environment. As previous research showed, social influence, especially opinions of important others, may have an impact on technology acceptance and the intention to use this technology (see Venkatesh et al., 2003).

Regarding the technical configuration of highly automated driving functions, these findings provide a first orientation for the parametrization by quantifying in numbers when passengers want the highly automated vehicle to start braking when approaching a junction. Within the obtained range of distance and time headway to the stop line, passengers perceive the braking maneuver as unpleasant at most, but not as dangerous.

9.4.2 Perceived risk

Overall, the majority of perceived risk ratings were located within the lower half of the scale (see Figure 62). So, passengers rated most of the interactions with vulnerable road users as *harmless* to *very unpleasant*, but not as *dangerous*. At the ideal braking onset time, perceived risk ratings ranged from *harmless* to *a little dangerous*, with 50 % (50 km/h) to 63 % (30 km/h) of the interactions being rated as *harmless*, and 96 % (50 km/h) to 98 % (30 km/h) of the interactions being rated as unpleasant at maximum. At the last accepted braking onset, perceived risk ratings ranged from *harmless* to *medium dangerous*, with 12 % (50 km/h) to 25 % (30 km/h) of the interactions being rated as *harmless*, and 77 % (30 km/h) to 78 % (50 km/h) of the interactions being rated as unpleasant at maximum.

These results indicate that, ideally, passengers aim to avoid or minimize an expected risk in an interaction with vulnerable road users. Accordingly, the passengers stopped the videos at an early stage so that they perceived the interaction as *unpleasant* at most, but not as *dangerous*. This kind of risk controlling behavior is in line with the basic idea of the *Zero Risk Theory* (Näätänen, & Summala, 1974, 1976; Summala, 1988), which assumes that drivers control risks by maintaining large temporal and spatial distances (safety margins) from potential hazards, resulting in drivers not experiencing risk at all. Regarding this interpretation, it should be noted that "risky" interactions are equated with the "dangerous" range on the applied perceived risk scale (see Figure 6).

Based on the obtained results, the *Risk Homeostasis Theory* (Wilde, 1982) is rejected as most passengers' target level of perceived risk is (close to) zero. So, there are no risk levels as that need to be balanced as passengers avoid risky interactions in the first place. But why do humans as passengers inside highly automated vehicles want to avoid risks?

This finding may in part be explained by the fact that human drivers have no experience as passengers in a highly automated vehicle yet. So, it is reasonable to assume that drivers take a cautious approach, and initially may want to be driven defensively, i.e. with an early braking onset when approaching a junction. With an increasing amount of (positive) experience with these systems, passengers' might prefer to be driven in a more dynamic way. So, in the long run, it could be speculated that there may be habituation effects causing passengers to take greater objective risks without experiencing this (objective) increase in risk. This effect would be consistent with the idea of the *Zero Risk Theory* (Näätänen, & Summala, 1974, 1976; Summala, 1988). Following this reasoning, passengers' preference may be subject to change, and the obtained results in the present study may be a snapshot capturing passengers' initial preference. Whether, and to what extent the preferences of passengers with regard to the driving behavior of an automated vehicle may change is the subject of further research.

9.4.3 Limitations

The present study is subject to a number of limitations. To begin with, the present study was conducted as an online video study instead of a driving simulator study. A major disadvantage of this online setting may be a reduced immersion compared to the driving simulator setting (see Bubb, 2015 for more background on immersion). It is hypothesized that the impression of being in a "real" driving situation was reduced substantially when watching videos compared to experiencing the same driving situation in the driving simulator. It is therefore possible that this reduced immersion has led to an underestimation of passengers' perceived risk in the interaction with vulnerable road users.

In addition, the presentation of the videos may have varied depending on participants' computer screen sizes, display resolution, and color rendering. These technical restrictions could have affected participants' perception, making it more difficult for participants to correctly estimate the ego-vehicle's distance to the stop line in the video. This may, in turn, have led to small selected distances to the stop line at the ideal braking onset time, and especially at the last accepted braking onset time. Due to these limitations, the braking onset times should rather be seen as a first orientation than a clear recommendation for the design of highly automated driving functions in this driving situation. Still, the results obtained in this online study provide a good basis for further testing in the driving simulator and in the field.

Furthermore, there was no experimenter present to supervise the experimental environment in the present online study, for example, to check whether participants understood the instructions correctly. Although participants were asked to complete the present study on a laptop or tablet in a quiet environment, it is unclear to what extent participants complied with this request. Therefore, the obtained results of Study 4 are planned to be validated in a supervised experimental environment in a driving simulator study at the Department of Traffic and Engineering Psychology at Technische Universität Braunschweig: However, this validation study is outside of the present dissertation's scope.

Apart from the limitations applicable to the experimental environment and procedure, the present study included only the braking onset as a feature of automated driving behavior. So, the present study neglected other relevant parameters in the braking maneuver, e.g., jerk, pitch or the deceleration strategy (see Dietrich et al., 2020). So, it is necessary to examine how passengers perceive (a combination of) these features of the braking maneuver. In this context, Ackermann et al. (2019, p. 766) suggested that there might not be a "one-fits-all braking algorithm" in the technical configuration of automated vehicles. So, the configuration of acceptable automated braking maneuvers might be complex and allow for some variation depending on individual preferences and situational factors.

As in the previous Study 3 (see Chapter 8.6), a major limitation of the present study was the lack of physical feedback from the brake reaction as participants only experienced the driving situation visually through the videos. However, physical feedback is a decisive factor in in passenger comfort during highly automated driving (see e.g., Bellem et al., 2018; Elbanhawi et al., 2015). Previous studies on passenger comfort during highly automated driving found that passengers feel most comfortable during automated driving when the lateral and longitudinal acceleration as well as jerk are low (e.g., Bellem et al., 2018; Griesche et al., 2016). Therefore, the obtained results are planned to be further validated in a field study on a test track using a vehicle-in-the-loop prototype (for more background see Bock et al., 2007; Bubb, 2015; Solmaz et al., 2020; Tettamanti et al., 2018).

9.5 Conclusion

Summing up, Study 4 provides evidence that passengers in an automated vehicle want to avoid *experiencing* risk when interacting with vulnerable road users at an urban junction. This result is consistent with the zero risk theory (Näätänen & Summala, 1974, 1976; Summala, 1988). In addition, the results obtained provide a first orientation for the technical configuration of highly automated driving behavior in this driving situation, with this configuration of automated driving behavior being perceived by passengers at most as unpleasant, but not dangerous. Automated driving behavior that passengers perceive as risky or dangerous may potentially compromise passengers' willingness to let themselves be driven automatically.

10 Final discussion

This dissertation aimed to understand how humans react to highly automated vehicles in mixed traffic on highways and in urban areas, taking into account the outside perspective of human drivers in non-automated vehicles, and the inside perspective of passengers in highly automated vehicles. The outside perspective was examined for highly automated driving on highways as this is the driving environment where these functions will first be introduced in the near future (Audi, 2017; Daimler, 2019; VDA, n.d.; see also Hetzner, 2020; Holzer, 2020). Study 1 examined the short-term perspective (first contact) whereas Study 2 addressed the mid-term perspective with repeated contact and an increasing proportion of highly automated vehicles in mixed traffic. As the inside perspective of passengers has already been extensively examined for the highway environment (see Vogelpohl et al., 2016 for a literature review), the first two studies focused on the outside perspective of human drivers in mixed traffic on the highway.

The next step of development will be the expansion of highly automated driving into urban areas (Tabone et al., 2021). Human factors research has just begun to investigate how highly automated vehicles will interact with pedestrians (e.g., Ackermann et al., 2019; Beggiato et al., 2018; Dietrich et al., 2020; Fuest et al., 2018, 2019; Lagström & Lundgren, 2015; Lundgren et al., 2017) and cyclists (e.g., Fritz, 2020; Mayerhofer, 2020; Stange et al., submitted). Thus, two additional studies were conducted in the present dissertation, examining how automated vehicles should operate in interactions with pedestrians and cyclists in two "standard" driving situations in urban areas. The research questions were how passenger want to be driven and whether passengers would accept some perceived level of risk (as assumed in *Risk Homoeostasis Theory*; Wilde, 1982) or tend to avoid risk at all (*Zero-Risk Theory*; Näätänen & Summala, 1974, 1976; Summala, 1988). Besides providing input for the human-centered development of automated driving functions in urban environments including interactions with vulnerable road users, the dissertation also contributes to the debate about the level of risk acceptable to human drivers or passengers in highly automated vehicles.

As highly automated driving functions are not yet available on the market (see Hetzner, 2020; Holzer, 2020), the idea of this dissertation was to examine human driver reactions in the driving simulator where highly automated driving functions can be implemented without being fully developed or even ready for production (see Bubb, 2015). To this end, three driving simulator studies and an online study using pre-recorded videos from the driving simulator were conducted in which humans experienced highly automated driving behavior in mixed traffic. Highly automated driving functions were implemented on the basis of expert interviews (Study 1, Study 2), and in close cooperation with function developers (Study 3, Study 4). Thus, it was possible to model highly automated driving behavior as an approximation real-world automated driving behavior. Using driving simulation as a methodological approach also allowed to capture spontaneous reactions which were analyzed on a subjective level (by means of questionnaire data), and on an objective level (by means of driving data). Across all four studies, the focus was on humans' subjective experience of safety, risk, and comfort. On the objective level, the studies addressed the safety-criticality of mixed traffic interactions.

Thus, the present dissertation contributes to create a more differentiated picture of how humans react in interactions with highly automated systems in mixed traffic.

The following Chapter 10 provides the final discussion of the results obtained in the four studies presented in the preceding Chapters 6, 7, 8, and 9. First, the major findings are summarized for the outside perspective of human drivers in mixed traffic (Study 1 & 2) and the inside perspective of passengers in mixed traffic (Study 3 & 4). Based on these findings, lessons learned, limitations and open research questions for future research activities are presented for the two parts of this dissertation separately (Chapter 10.1 / 10.2). Finally, an overall conclusion is drawn (Chapter 10.3).

10.1 Human as drivers in mixed traffic

The first part of this dissertation illuminated the outside perspective of human drivers in non-automated vehicles in mixed traffic interactions on the highway as the introductory scenario for Level 3 driving functions. To this end, expert interviews were conducted to identify relevant driving situations where human drivers will first interact with these vehicles (see Chapter 6.2.1.1), to understand the typical driving behavior of these vehicles (see Chapter 6.2.1.2), and to gain knowledge of how highly automated vehicles will look like (see Chapter 6.2.1.3). Based on the expert statements, two driving simulator studies were conducted to gain insights on how human drivers interact with and react to these highly automated vehicles, the focus was on human drivers' first contact with these vehicles (Study 1), and in repeated interactions during longer highway trips (Study 2).

10.1.1 Major findings (Study 1)

In Study 1, human drivers experienced four driving scenarios in mixed traffic (see Table 1) covering two types of interactions: (1) a target vehicle reacting to a preceding human driver, (2) a human driver reacting to a preceding target vehicle. Study 1 addressed the main research question of how human drivers react to highly automated vehicles at first contact with these vehicles in mixed traffic on the highway (see Chapter 5). Specifically, the focus was on the external distinguishability of highly automated and human-driven vehicles in mixed traffic (RQ 1.1) and human drivers' perceived safety and comfort (RQ 1.2) as well as the objective safety-criticality of mixed traffic interactions (RQ 1.3). Further, the effect of an external labelling of highly automated vehicles on human drivers' reactions was examined (RQ 1.4).

Study 1 (see Chapter 6) showed that human drivers are able to identify rule-compliance and large safety margins as key features of highly automated driving behavior, and thus are able to identify from an outside perspective whether a vehicle was in highly automated driving mode or being driven by a human driver in the examined driving situations in most cases (RQ 1.1). These results are in line with the presented hypotheses (see Chapter 6.1), providing evidence that human drivers already have an adequate idea of how highly automated vehicles in dyadic mixed traffic interactions. In addition, human drivers rated interaction with highly automated vehicles as safe and pleasant as interactions with human-driven vehicles (RQ 1.2). Possibly, this effect could be explained by to a defensive driving style rather than the highly automated driving mode of the vehicle, since human-driven target vehicles with a defensive driving style were rated similarly positively. Thus, human drivers appreciated the defensive driving style during dyadic interactions in general. Regarding the objective criticality of mixed traffic interactions, however, the study showed that the type of interaction had a significant impact (RQ 1.3). In particular, driving situations in which human drivers had to react to the strictly rule-compliant driving behavior of a preceding highly automated vehicle led to surprise effects among human drivers, resulting in small safety margins (as measured by minimum time headway). Based on these findings, it was hypothesized that an external labelling a vehicle’s current driving mode might help to diminish these surprise effects in the long run (RQ 1.4). However, the present study revealed no immediate safety-related benefit of such an external labelling in dyadic mixed traffic interactions beyond being of mere informational value.

10.1.2 Major findings (Study 2)

As the scope of Study 1 was limited to human drivers’ very first contact with highly automated vehicles, experiencing short interactions in four selected driving situations, a second driving simulator study was conducted to provide further insights into how drivers react to driving in mixed traffic with increasing penetration rates of highly automated vehicles on entire highway sections during longer trips. The highway sections included the two interaction types from Study 1, and thus were limited to the driving situations which highly automated vehicles of the first generation were expected to master independently. To further enhance proximity to real-world driving, human drivers were encouraged to drive as they usually would in their own vehicles. Study 2 addressed the main research question of how human drivers react to highly automated vehicles during the simulator drive in mixed traffic (see Chapter 5). In particular, Study 2 focused on the external distinguishability of highly automated and human-driven vehicles (RQ 2.1), and human drivers’ perceived safety (RQ 2.2), comfort (RQ 2.2) and emotions (RQ 2.3). Furthermore, Study 2 explored highly automated vehicles’ potential role model function for human drivers in terms of rule-compliance (RQ 2.4), as well as human drivers’ behavioral adaptation to an increasing penetration rate of highly automated vehicles in mixed traffic (RQ 2.5). In addition, the potential benefits and issues of an external labelling of highly automated vehicles were further investigated (RQ 2.6).

Study 2 (see Chapter 7) provides evidence that highly automated vehicles have no role model effect for human drivers in terms of rule-compliance and defensive driving (RQ 2.5). Although a significant reduction in the speed of human drivers was achieved with increasing penetration rates (particularly noticeable from 50 %) of highly automated vehicles, this positive effect was levelled out by frequently occurring short time headways of human drivers to preceding vehicles (RQ 2.4). These findings highlight that human drivers did not simply imitate the driving behavior of surrounding highly automated vehicles – even after some exposure time. The negative consequence of an increasing penetration rate of highly automated vehicles was also reflected in the subjective ratings regarding perceived efficiency as well as perceived safety and comfort (RQ 2.2), but not on an emotional level (RQ 2.3). Specifically, human drivers rated driving in mixed traffic significantly more unpleasant compared to non-automated traffic (RQ 2.2). This effect was already apparent at a penetration rate of 25 % highly automated vehicles in mixed traffic. Regarding the distinguishability of highly automated and human-driven vehicles in mixed traffic, an accurate estimation of the penetration rate was only possible if the current highly automated driving mode was labelled (RQ 2.1). On longer highway sections, driving behavior alone as a visual cue was insufficient to identify a vehicle's driving mode correctly. Based on this finding, it was hypothesized that behavior beyond the scope of the present study, an external labelling could be useful to form an accurate mental model to anticipate highly automated driving behavior correctly in the long run (RQ 2.6).

10.1.3 Lessons learned: Humans as drivers in mixed traffic on the highway

This section presents the present dissertation's contribution to the question of how human drivers react to Level 3 vehicles in mixed traffic on the highway. In addition, the psychological question of the role of correct expectations and mental models in interaction with highly automated vehicles in mixed traffic is addressed.

Overall, human driver reactions to highly automated vehicles were positive in first contact in Study 1, with dyadic interactions with highly automated target vehicles in the selected driving situations being rated as safe and pleasant as interactions with other human drivers. So, human drivers perceived the defensive and rule-compliant highly automated driving style as positive. At the same time, however, the present dissertation also provides evidence that this defensiveness and rule-compliance is to some extent double-edged. Whereas human drivers perceive this behavior as pleasant and safe in dyadic interactions (Study 1), similar configurations of automated driving behavior were rated as unpleasant during longer highway trips (Study 2). So, human drivers rather perceived highly automated vehicles as obstacles resulting in partly safety-critical interactions, especially during longer highway trip in mixed traffic (Study 2). Nevertheless, this effect became most evident at higher penetration rates of 50 % or 75 % automation in mixed traffic which may first become relevant in the distant future based on the presented estimations of equipment rate in chapter 2.2 (see Figure 2).

Moreover, the present dissertation showed that highly automated driving behavior is noticeably different than human driving behavior. In this context, previous research suggested to program highly automated driving behavior more human-like to close the gap between human drivers' expectations and highly automated vehicles' actual driving behavior (Nyholm & Smids, 2020). However, human drivers may engage in illegal driving behaviors, so it might be reprehensible to program automated systems displaying such behaviors in a systematic way (see Nyholm & Smids, 2020 for more discussion).

In the dyadic interactions examined in Study 1, human drivers were able to distinguish highly automated vehicles from surrounding human drivers on the basis of their different driving behaviors alone. This finding also supports the suggestion by Fuest et al. (2020) that driving behavior itself may be sufficient as a visual cue to identify highly automated vehicles on highways. However, in repeated interactions with highly automated vehicles (Study 2), human drivers relied on the external labelling of the vehicle's current driving mode as a visual cue to distinguish highly automated vehicles from human-driven vehicles. Based on this result, an external labelling of the current driving mode may be recommendable to allow for an unambiguous identification of a vehicle's current driving mode. Based on this information, human drivers can learn how highly automated vehicles operate, and anticipate the development of a driving situation including the highly automated vehicle's future actions accurately (see Endsley, 1995a), thereby contributing to solve space-sharing conflicts in mixed traffic successfully.

Arguably, an external labelling of the current highly automated driving mode alone may not be enough to diminish safety-critical interactions as the obtained results from both Study 1 and Study 2 show. In order to support successful coordination of space in mixed traffic, previous human factors research has identified the need for user education and training to support passengers as users of the highly automated system to form accurate mental models of the highly automated system's capabilities (see Forster et al., 2020). The results obtained in the present dissertation indicate that it may be useful to expand the target group of such user education to human drivers in non-automated and assisted vehicles (up to SAE Level 2) as a preventive measure to reduce the number of safety-critical interactions with these systems in first contact (Study 1). Possibly, human drivers would maintain larger safety margins to preceding highly automated vehicles if drivers knew about the vehicles' rule-compliant driving behavior prior to the first interaction. A combination of education, external labelling of the current driving mode, and repeated interactions to gain experience with this technology may diminish “surprise” effects caused by unanticipated driving behavior, and promote correct anticipation of future driving maneuvers. As a first use-case in which a potential hazard could be mitigated by an external labelling is the type of interaction where human drivers have to react to the driving behavior of highly automated vehicles in front (S03 / S04 in Study 1). As previous traffic collision reports and crash analyses of mixed traffic accidents have shown, rear-end collisions are most frequent type of accident (California Department of Motor Vehicles, 2021; see Boggs et al., 2020; Teoh & Kidd, 2017).

10.1.4 Methodological reflection

Study 1 and Study 2 were conducted in a static driving simulator. Thus, human drivers could experience highly automated driving and interact with these vehicles in mixed traffic at an early stage of development of highly automated systems (see Bubb, 2015). In addition, driving simulator studies offer the possibility to investigate effects of mixed traffic on human drivers in a safe driving environment (see de Winter et al., 2012). In the simulated driving environment, a variety of driving scenarios can be created. Within these scenarios, it is easy to adapt and reproduce individual components including the infrastructure and the driving behavior of the simulated vehicles in a systematic way (see de Winter et al., 2012). This exact modeling of the scenarios and their reproducibility were crucial for the investigation in Study 1 to ensure that all participants experience a nearly identical interaction. Such an exact reproduction of each driving scenario for all participants would have been difficult to achieve in an experimental set-up on a test-track or in real-world traffic. Similarly, the penetration rate of highly automated vehicles in Study 2 being as high as 75 % in mixed traffic would not be feasible under real-world driving conditions. These are two major advantages of driving simulator studies over other experimental environments when testing highly automated driving functions.

Due to the incomplete technical development of highly automated driving functions, however, a large number of assumptions had to be made regarding the driving behavior, external appearance of these highly automated vehicles and the relevant driving situations in which the highly automated driving function would be in operation. To this end, expert interviews were conducted in preparation of the two studies (see Chapter 6.2.1). However, the expert interviews only provided a snapshot of statements on current developments and considerations that may have changed in the course of further development of the technology. Therefore, the implementation of highly automated systems is always an approximation to reality based on the current state of knowledge. Regarding the aspect of assumed highly automated driving behavior, only a limited set of parameters of the driving function could be examined within the scope of this dissertation, namely, speed adaptation and time headways to surrounding vehicles (see Chapter 7.2.4) whereas the default options of the applied driving models were used for the other parameters.

In the light of the limited set of driving situations highly automated driving functions of the first generation are assumed to master with human intervention, this dissertation certainly could not cover all typical driving situations that occur frequently on the highway. The implemented driving scenarios and highway section had little complexity, and thus simplified the reality of road traffic to some extent. Therefore, the obtained results of the studies are not fully transferable to real-world driving. The generalizability of the obtained results is further limited by the lack real hazard potential in the experimental simulator setting. This may have led to an overestimation of perceived safety and comfort during the simulator drives.

It is therefore not possible to draw the general conclusions about the effects of the introduction of highly automated vehicles on traffic safety in mixed traffic on real-world highways. This general statement would require more detailed knowledge of the driving behavior of highly automated vehicles at the parameter level, as well as a more representative possible coverage of relevant driving situations. Since these two aspects have presumably developed further in the last three years since the expert interview were conducted, the two studies would have to be supplemented by possible new findings. However, the two studies provide initial insights into how human drivers handle the new technology and which driving situations in mixed traffic entail potential hazards.

Summing up, driving simulator studies have the potential to explore highly automated driving in mixed traffic at earlier stages of development but simulator studies are no replacement for driving studies using real vehicles on test track, and in the field at later developmental stages. In contrast to the safe driving simulator environment, however, real-world driving entails real hazard potential.

10.1.5 Limitations and future research activities

The results obtained in the first part of this dissertation are subject to a number of limitations and leave open questions for further research.

Firstly, Study 1 and Study 2 have focused on the human driver perspective in mixed traffic, whereas the passenger perspective inside the highly automated vehicle was not addressed. Thus, it is an open research question how a passenger would evaluate the highly automated driving behavior and the interactions with human drivers under identical experimental circumstances. As there was a substantial difference between human and highly automated driving behavior in the two studies, there is a chance that passengers could find the implemented highly automated driving style too defensive. Previous research has demonstrated that a cautious driving style may result in driver-induced take-overs to save time

(Techer et al., 2019). It would be interesting to examine the passenger perspective using the parameters from the previous Study 1 and Study 2 and compare the passenger reactions with the results presented in this dissertation from the external perspective of human drivers. In this context, multi-driver simulator study set-ups (e.g., Feierle et al., 2020; Mühlbacher, 2018; Preuk, Stemmler & Jipp, 2016; Preuk, Stemmler, Schießl et al., 2016; Preuk et al., 2018) could be modified as an economical tool to capture both passengers' and human drivers' perspectives simultaneously. However, there are some challenges attached to this experimental approach regarding study planning, experimental procedure and data analysis (see Feierle et al., 2020; Mühlbacher et al., 2018; Oeltze, & Schießl, 2015).

A second open question to be targeted in further research is the question how passengers inside the highly automated vehicle would evaluate an external labelling. The present dissertation provides evidence that displaying a vehicle's current driving mode can be useful for surrounding human drivers to distinguish highly automated vehicles from human-driven vehicles on longer highway sections while the passenger perspective was not addressed. It is reasonable to assume that passengers might feel stigmatized by the external labelling as human drivers may perceive the highly automated vehicle negatively, e.g., as an "obstacle". It is also conceivable that human drivers may show risky driving behaviors toward the highly automated vehicle in a systematic way, once human drivers can unambiguously identify the vehicle's differentness (e.g., Connor, 2016; Eliot, 2019; Stanton et al., 2020). This concern was, to some extent, supported by empirical evidence from the present dissertation but there was no systematic pattern or intentional bullying discerned from these findings. So, future research on external HMIs in mixed traffic should not only take the outside perspective of human drivers but also the passenger perspective into account.

Thirdly, it is yet to be explored how highly automated vehicles affect road safety in the long run, and how mixed traffic interactions with human drivers may change over time. The studies conducted in the present dissertation provide a first snapshot in the beginnings of mixed traffic interactions, however, the development of situation awareness including the correct projection of future driving behavior requires more learning experience (see Endsley, 1995a). In this context, the research question also arises, how many contacts are necessary for human drivers to build up a mental model in the context of situation awareness of how highly automated systems work? And to what extent can training and education facilitate this process? To explore these research questions, experimental studies using longitudinal designs provide a suitable methodological approach. In this process, it would also be interesting to find suitable measurements of human drivers' situation awareness in mixed traffic (see Endsley, 1995b).

A fourth open question is whether highly automated vehicles can serve as role model for human drivers. In this context, Study 2 examined whether human drivers could adapt the behavior of highly automated vehicles by imitating their strict adherence to traffic rules, driving slower, and keeping larger safety margins to surrounding vehicles. On a broader level, the question is whether, and to what extent, social learning (Bandura, 1977) takes places in mixed traffic interactions. If social learning was possible in mixed traffic, one would expect human drivers to adhere better to the traffic rules in terms of speed reduction while maintaining sufficiently large safety margins (> 1 s time headway) to preceding vehicles at the same time. This effect of rule-compliance could become stronger the higher the penetration rate of these vehicles in mixed traffic. In part, this effect was evident in Study 2 as human drivers' average speed reduced the more the penetration rate of highly automated vehicles had increased on the highway sections (see Chapter 7.3.3.1). At the same time, however, human drivers' safety margins to preceding vehicles decreased (see Chapter 7.3.3.2). Taking the reductions of speed and time headways into account, highly automated vehicles do not seem to act as role models for human drivers. Following this line of reasoning, it could be argued that social learning in the context of highly automated driving in mixed traffic is either not possible at all, or, that social learning is theoretically possible but did not occur due to the experimental design in Study 2.

For one, car driving is a skill that humans have developed, refined, and practiced over years, or decades. So, human drivers' driving style is habituated over time (Elander et al., 1993), and these behavioral patterns may be so stable that they cannot be changed within one experimental session in the driving simulator. The learning time of approximately 60 to 75 minutes (3 x 20 to 25 minutes) in mixed traffic may have simply been not long enough. To study behavioral changes, longitudinal studies would be a more suitable method.

In addition, it is questionable whether the highway driving environment offers enough dyadic interactions to enable social learning. In an urban environment, human drivers adapted their driving behavior to automated vehicles equipped with a traffic light assistant (see Preuk, Stemmler & Jipp, 2016; Preuk, Stemmler, Schießl et al., 2016; Preuk et al., 2018). Non-equipped human drivers maintained smaller time headway to preceding vehicles, thus increasing the efficiency of the traffic flow. This finding indicates that human drivers can imitate the driving behavior of surrounding vehicles in mixed traffic, but maybe not in the highway environment examined in the present dissertation.

Another obvious argument for the absence of social learning would be that human drivers recognized a vehicle's driving mode mainly on the basis of the external labelling (see Figure 20), so that participants in the groups without external labelling failed to identify the vehicle's driving mode correctly. However, participants' driving behavior, and subjective ratings were similar in all three experimental group depending on the penetration rate of highly automated vehicles, which implies that the presence of an external labelling had no effect here.

An alternative explanation for the lack of a role model function of highly automated vehicles for human drivers in mixed traffic is based on the *Theory of Planned Behavior* (Ajzen, 1985). According to this theory, humans plan behavior based on their personal *attitude* toward the behavior and *social norms*[1]. Thus, in order intend for a person to intent the performance of a certain behavior, this behavior needs to be evaluated positively by the performing person themselves, and by “important others” (Ajzen, 1985, p. 12). The essential questions in the context of mixed traffic are:

- Who are the “important others”, i.e. who belongs to the social reference group influencing human drivers’ intentions?
- Is highly automated driving behavior as experienced in the driving simulator evaluated positively (enough) by human drivers to be imitated?

So, one reason for the absence of social learning might be that human drivers may not include highly automated vehicles in their social reference group as “important others”. Instead, it is conceivable that human drivers have “humans” as a social reference group whereas highly automated vehicles are categorized as “non-human agents” or “machines”, thus being socially irrelevant for human drivers. Consequently, there is a different set of behavioral norms for these two separate groups. In the group of human drivers, it may be common to speed or maintaining small safety margins to preceding vehicles, whereas highly automated vehicles, belonging to the other social group, have to follow traffic rules more strictly. As a consequence, highly automated vehicles cannot serve as role models for human drivers because their behavior is not relevant for human drivers on a social level.

In this context, it should be mentioned that some (concept) cars have anthropomorphist features, such as a smile or eyes (e.g., “The Smiling Car” by Semcon, 2017; Chang et al., 2017; for more background on anthropomorphisms see Epley et al., 2007), potentially to make human road users bond with these vehicles on a social level. In a virtual reality study, pedestrians reported a higher level of safety and made correct crossing decision faster when crossing in front of an approaching automated vehicle with eyes compared to no anthropomorphist feature (Chang et al., 2017). So, anthropomorphisms may at least have some effect on human road users in the driving environment. In a broader human-machine interaction context, previous research suggests that humans may be able to imitate the

[1] Arguably, there are more determinants of planned behavior than the social aspects mentioned in this dissertation (see Ajzen, 1985; see also Fishbein & Ajzen, 1975, 2010). Nevertheless, future research may take these theoretical considerations into account when addressing the question of what human drivers can or cannot learn from highly automated vehicles in mixed traffic.

behavior of non-human robots to a somewhat limited extent (Zanatto et al., 2020). So, there might be a chance that the imitation of highly automated driving behavior as a social learning strategy is possible even without “humanizing” the appearance of these vehicles.

At the same time, it is well known from social learning theory (Bandura, 1977) that not every (human) agent acts as a role model in social learning. Instead, social learning is guided by the idea that a specific action increases the probability of *anticipated* positive outcomes. On a social level, behavior is reinforced by observing how others being rewarded (vicarious reinforcement) or punished (vicarious punishment) for their actions. Here, observation alone is not sufficient because humans need to understand the cause that the cause of the outcome is specific behavior performed by an automated vehicle rather than other external circumstances. This is not solely a question of observation but rather a question of (correct) attribution. Applying this theoretical foundation of the social learning theory (Bandura, 1977) to the context of mixed traffic on the highway, human drivers need to learn that the driving behavior of highly automated vehicles increases the probability of a positive outcome in order for social learning to take place. In traffic, however, drivers rather experience punishment for rule-breaking behavior, e.g., getting fined for speeding, than receiving rewards for rule-compliant or even cooperative behavior, although cooperation between human road users exists to some extent (see Powelleit et al., 2018; 2020). In the context of mixed traffic, a tangible example for a positive outcome is not getting fined. For social learning to be successful, human drivers need to observe that highly automated vehicles are not fined because of their rule-compliant driving behavior. After repeated learning experiences, human drivers might realize that it is advantageous to behave as rule-compliant as highly automated vehicles do. The question would be how much learning time or number of interactions human drivers need. At the same time, it is questionable how beneficial the imitation of rule-compliant behavior is for human drivers as their own driving goals may be too strong. Thus, it is possible that automated driving behavior is not evaluated positively (enough) because it interferes with human drivers’ goal to avoid deceleration and to reach their destination timely (Summala, 2007).

So, future research needs to disentangle the questions:

- Are human drivers not able to imitate highly automated driving behavior due to their own habitual patterns of driving behavior, or is highly automated driving behavior as a prototype of rule-compliance not desirable enough because the potential avoidance of negative consequences has too little perceived advantage for human drivers?
- What are the relevant aspects in experimental environments, e.g., exposure time, reinforcement, which could promote social learning from highly automated vehicle?

10.2 Humans as passengers in mixed traffic

The second part of this dissertation focused on passenger comfort and perceived risk during highly automated driving (Level 4, SAE, 2014, 2018). In particular, the focus was on interactions with vulnerable road users in urban mixed traffic. To this end, two basic urban driving situations, including an obstructed path (Study 3) and a crossing paths (Study 4) space-sharing conflict (Markkula et al., 2020) were implemented in the driving simulator. In these two space-sharing conflicts, highly automated driving behavior was configured in cooperation with function developers from Technische Universität Braunschweig. Based on these preparations, a driving simulator study (Study 3) and an online video study (Study 4) were conducted.

10.2.1 Major findings (Study 3)

Study 3 addressed the main research question of how passengers want to be driven in a highly automated vehicle in longitudinal mixed traffic, when passing a pedestrian on a parking stand. To answer this research question, a driving simulator study was conducted. In the first part, passengers' perceived risk and comfort were measured depending on variations in highly automated driving parameters (speed, lateral offset, deceleration) and the presence of a pedestrian on the parking stand and oncoming traffic (RQ 3.1). In the second part, participants completed four conditions of the driving scenario manually in a way they considered *ideal* highly automated driving behavior in this driving scenario (RQ 3.2).

The first major finding of Study 3 (see Chapter 8) was that passengers aimed to maintain large and increase safety margins to potential hazards (pedestrian, oncoming traffic, parked vehicles) if possible. From this finding, it could be concluded that an adaptation of the vehicle's trajectory is useful as this adaptation helps passengers to stay within their comfort zone. The more the adaptation deviated from this goal to enlarge the large safety margin, the more negative was passengers' evaluation of this driving behavior in terms of perceived risk and comfort (RQ 3.1). Regarding the pre-defined configurations of highly automated driving behavior, the study provides evidence that human drivers perceived the variations mostly pleasant and comfortable, on average, but not as dangerous.

Secondly, trajectory adaptation can be a form of feedback for the passenger, that the system has detected the relevant features in the driving environment, e.g., the pedestrian approaching the edge of the road, and that the system is reacting flexibly and safely to the pedestrian. At the same time, human road users in the driving environment can benefit from a visible trajectory adaptation, as they also receive feedback that they have been detected by the highly automated vehicle.

Finally, the study provides some initial ideas for the parametrization of an adapted trajectory. Subjective passenger ratings revealed that the examined pre-defined configurations of the lateral offset (± 0.5 m from the center of the lane), deceleration (≈ 1 m/s^2), and vehicle speed (= driving the maximum permitted speed) were already well-suited. However, the second part of the study also showed that the deceleration strength and the lateral deviation from the center of the lane could be even weaker or smaller, respectively, than in the presented configurations in Part I (RQ 3.2).

10.2.2 Major findings (Study 4)

Study 4 further explored the main question of how highly automated vehicles should drive in urban mixed traffic interactions with vulnerable road users. In particular, Study 4 focused on a space-sharing conflict when approaching an urban junction with crossing pedestrians and cyclists. To examine this research question, an online video study using pre-recorded videos from the driving simulator was conducted. Passengers initiated the vehicle's braking maneuver by stopping the video at the point in time passengers considered ideal (RQ 4.1) and at a point in time passengers considered to be the last, acceptable (RQ 4.2) braking onset time. After each interaction, participants rated perceived risk (RQ 4.3).

As a major result, Study 4 found that passengers' preferences regarding the timing of the braking onset times were highly individual. However, passengers shared the common goal to avoid experiencing risk in the interaction with vulnerable road users at an urban junction (RQ 4.3). At the ideal braking onset, passengers triggered the highly automated vehicle's braking onset well before the junction, so that the braking maneuver was smooth and comfortable whereas at the last, acceptable braking onset, most passengers accepted unpleasant, but not dangerous interactions (RQ 4.1 / RQ 4.2). In the 30 km/h condition, passengers wanted the highly automated vehicle to ideally start braking, on average, 31 m (3.7 s time headway) before the stop line, and at the latest, on average, 21 m (2.6 s time headway) before the stop line. In the 50 km/h condition, on average, passengers wanted the highly automated vehicle to ideally start braking, on average, 51 m (3.8 s time headway) before the stop line, and at the latest, on average, 31 m (2.6 s time headway) before the stop line. These large distances and time headways the stop line allow for smooth and comfortable braking maneuvers. Finally, the obtained results provide some initial ideas for the configuration of speed-dependent braking onset timing for the development of highly automated driving behavior in similar interactions at junctions, especially within the speed range between 30 km/h and 50 km/h.

10.2.3 Lessons learned: Humans as passengers in urban mixed traffic

This dissertation provides insights into passengers' perceived risk and comfort during automated driving as well as practical implications for the configuration of highly automated driving functions. Based on driver-related psychological risk theories and findings of previous research on comfort experience (see Chapter 4), two studies were conducted. The driving situations investigated in this dissertation each placed very different demands on the automated system. The adaptive approach of the measurement methodology (Study 3, Part II; Study 4) made it possible to map passengers' perceived risk in detail. Thus, the dissertation took up the psychological debate on the optimization of the risk in driving (see Fuller, 2000, 2005, 2011; Näätänen & Summala, 1974; Wilde, 1982) and transferred it to the passenger perspective in the highly automated driving context.

Overall, the present dissertation showed that passengers want to avoid experiencing risk in interactions with vulnerable road users in urban mixed traffic. The ratings in the studies were located in the lower half of the perceived risk scale, ranging from harmless to very *unpleasant*, with only a few exceptions, where interactions were rated as *dangerous*. Thus, the mean values reach the lower limit of the *dangerous* range at maximum, i.e. the edge of perceived risk as measured by the perceived risk scale. These findings provide some backing for the *Zero Risk Theory* (Näätänen & Summala, 1974, 1976; Summala, 1988) and the task difficulty driving model (Fuller, 2000, 2005, 2011) while rejecting the *Risk Homeostasis Theory* (Wilde, 1982) as passengers do not experience risk while being driven automatically. Instead, the present dissertation showed that passengers aimed to optimize task difficulty within their comfort zone (Summala, 2007).

Regarding the technical configuration of highly automated driving functions, the obtained results provide function developers with some ideas of the range of accepted behavior in the examined driving situations. In this context, a key finding is that acceptance of passengers can be achieved by many different configurations as there may be more than one appropriate reaction to the driving environment. For example, in Study 3, passengers found it acceptable that the highly automated vehicle drove a lateral offset to the left as a reaction to the pedestrian in the parking stand if there was no oncoming traffic. At the same time, driving without a lateral offset was equally well accepted. So, vehicle kinematics helped to enhance passenger comfort and mitigate perceived risk, thus supplementing internal HMIs (see Hartwich et al., 2020).

Moreover, the empirical distributions of the preferred braking onset timings in Study 4 (see Figure 64) showed that preferences regarding the ideal braking onset were highly individual, although passengers seemed to have a common goal of avoiding risk. Therefore, it seems reasonable to allow some adaptation of highly automated driving behavior by passengers in addition to a standard defensive driving style as suggested by previous research (e.g., Beggiato et al., 2017; Dettmann et al., 2021; Griesche et al., 2016; Ossig et al., 2021; Scherer et al., 2016).

10.2.4 Methodological reflection

Study 3 was conducted in a fixed-base driving simulator whereas Study 4 was carried out online. The most prominent limitations of the two experimental environments were already outlined in the study-specific discussion sections in Chapters 8.6 and Chapter 9.4.3. Instead, this methodological reflection focuses on the measurement of perceived risk in the two studies.

In the two studies, the perceived risk scale (see Figure 6) using the instructions described in Chapter 8.3.2.1 was applied. A major methodological limitation regarding the applied risk scale is the fact that participants were asked to rate perceived risk of the *driving situation* as a whole instead of rating the highly automated vehicle's *driving behavior* within the driving situation. This lack of precision was compensated, to some extent, by relocating the focus of subjective ratings on specific features of the highly automated driving behavior. In Study 3, for example, there were additional questions regarding the vehicle's speed, and lateral distance to hazards in the driving environment. Thus, it was still possible to gain differentiated insight into how passengers had perceived the highly automated vehicle's reaction to the driving environment. In Study 4, the focus was on braking onset as one single feature of highly automated driving behavior.

A second major methodological limitation refers to the measurement procedure of the perceived risk scale in Study 3. Here, passengers first rated pre-defined configurations of relevant parameters and then were asked to drive manually in a way they considered ideal for an automated driving function. This is a major limitation as it is difficult for participants to perform specific, accurate driving maneuvers in the driving simulator. Furthermore, participants neither evaluated their own drive, nor did participants experience their own drive in replay from the passenger's perspective. Consequently, it remains unclear whether participants at all considered their own driving behavior as *ideal* (highly automated) driving behavior in the given variation of the driving scenario. The obtained results from the recorded driving data hint human drivers' goal to maintain safe margin to the oncoming traffic as well as to the parked vehicle. These findings support the idea of the *Zero Risk Theory* (Näätänen & Summala, 1974, 1976; Summala, 1988) as already discussed in Chapter 8.4. However, this interpretation is only valid if the manual drive was indeed *ideal* for passengers in this driving situation.

On the contrary, the adaptive measurement of perceived risk used in Study 4 where passengers manually triggered the vehicle's braking maneuver being in the passengers' role throughout the entire study proved to be a better way to examine how much perceived risk passengers are willing to accept. This procedure allowed to explore both passengers' preferences, and their perceived risk threshold.

Finally, the experimental test settings (driving simulator, online video study) further limit the generalizability of the obtained results as human drivers were aware of the experimental environment and knew that they were safe at all times. This may have led to an overestimation of perceived risk and comfort. Nevertheless, driving simulator studies may be the first step to explore human reactions to highly automated driving at earlier stages of technological development (see Bubb, 2015), if the driving function is not yet fully functional as in the studies presented in this dissertation.

10.2.5 Limitations and future research activities

In addition to the methodological restrictions, the results obtained in the second part of the present dissertation are subject to a number of limitations and leave open question for further research.

To begin with, the driving scenarios examined in Study 3 and Study 4 were subject to simplification, e.g., pedestrian and cyclist behavior were standardized in the two studies. As a result, the driving scenarios may have lacked proximity to reality. Therefore, the obtained results regarding passengers' perceived risk and comfort as well as the recommendations for the technical configuration of highly automated driving functions are limited to these specific urban driving situations. In addition to the specific driving situations, the experimental environment (online study, driving simulator, field / test-track study) may also have a strong impact on the parameter values (Dettmann et al., 2021). So, simulator studies or studies using pre-recorded simulator videos may not a replacement for driving studies in the test-track, and in the field at later developmental stages.

Further research can easily increase the proximity to reality by adding complexity, extending the driving scenarios by one or more of the following aspects: (1) static or moving obstacles being located in the lane of the highly automated vehicle, (2) other road types such as shared spaces, and (3) environmental factors: including different times of day with different lighting conditions. In longitudinal traffic (Study 3), the effect of moving or static obstacles in the lane of the highly automated vehicle would be interesting to study as the vehicle's trajectory was not directly impaired by any obstacle in Study 3. It is reasonable to assume that perceived risk would be higher if the highly automated vehicle was on a direct collision course with the pedestrian. In the junction situation (Study 4), the effects of visual obstruction by parked vehicles, as well as a more complex infrastructural design on mixed traffic interactions would be interesting to study. However, the investigation of such complex interactions requires a more advanced state of technical development, so that realistic assumptions on the parameter values can be made for an investigation in the driving simulator.

A more advanced stage of technical development would enable future research to examine entire automated trips inside urban areas instead of isolated driving situations in mixed traffic. In this context, a driving destination of personal relevance could create more proximity to real-world driving as humans often need to reach a certain destination of travel within a limited time frame. Therefore, time pressure may have a major impact on passengers' preference regarding highly automated driving behavior. First insight from previous research showed that time pressure did increase the number of passenger-induced take-overs, although not significantly (Techer et al., 2019).

Moreover, the present dissertation neglected the vulnerable road user's perspective in the examined driving scenarios. Assuming that highly automated driving will only become established in urban road traffic if all road users involved accept this new technology, it is essential to include the perspective of vulnerable road users in the investigation of urban mixed traffic as well. A multitude of studies provide insights into the perspective of pedestrians in interactions with automated vehicles in urban mixed traffic (e.g., Ackermann et al., 2019; Beggiato et al., 2018; Dey et al., 2019; Dietrich et al., 2020; Fuest et al., 2018, 2019; Lagström & Lundgren, 2015; Lundgren et al., 2017; Rothenbücher et al., 2016) whereas the perspective of cyclists is yet understudied (Fritz et al., 2020), with only a few studies available thus far (e.g., Hagenzieker et al., 2020; Hou et al., 2020; Kaß et al., 2020; Stange et al., submitted). Previous experimental studies were conducted using video simulation (e.g., Ackermann et al., 2019; Baggiato et al., 2018), (virtual reality) pedestrian simulators (e.g., Dietrich et al., 2020; Fuest et al., 2019; for a review see Schneider & Bengler, 2020) and bicycle simulators (e.g., Hou et al., 2020; Kaß et al., 2020; Stange et al., submitted), or in the field (e.g., Dey et al., 2019; Fuest et al., 2018). Beyond these single perspective approaches, multi-simulator studies with linked simulator environments could be useful tools to capture spontaneous reactions of drivers (or passengers) and vulnerable road users simultaneously (see Lehsing et al., 2016).

10.3 Conclusions

This dissertation investigated how humans react to highly automated vehicles in mixed traffic on the highway and in urban areas, taking into account both the inside perspective of a passenger and the outside perspective of human drivers.

Across all four studies, it became evident that highly automated vehicles drive differently than human drivers, and that humans as passengers and drivers in mixed traffic notice these differences while interacting with these vehicles. Nevertheless, human drivers and passengers perceived highly automated driving behavior as unpleasant at maximum, but not as dangerous.

From the outside perspective, human drivers perceived the interactions with highly automated vehicles as safe and as pleasant as interactions with other human drivers although human drivers were surprised by the rule-compliance of highly automated vehicles in first contact. However, rule-compliance can lead to human drivers feeling impaired in their progress of trip (Summala, 2007), which, in turn, may lead to safety-critical interactions with highly automated vehicles. Moreover, an external labelling of highly automated vehicle's current driving mode proved useful for human drivers in the long run but it is yet to the be studied how passengers perceive being driven in an externally labelled vehicle.

From the passenger perspective, the major finding of this dissertation is that passengers want to avoid risk when being driven automatically in the urban mixed traffic, supporting the *Zero Risk Theory* (Näätänen & Summala, 1974, 1976; Summala, 1988). Most important for passengers is an early feedback from the highly automated system, and a behavioral adaptation proving that the automated system has understood the relevant features of a driving situation in order to contribute to solving the space-sharing conflict with other human road users. However, the present dissertation also showed that "zero risk" can be achieved by more than one technical configuration of highly automated driving behavior as there are individual differences in how passengers perceive these configurations. So, this dissertation provides some ideas regarding the technical configuration, and developers should take passengers' risk aversion into account to preserve passengers' willingness to let themselves be driven automatically.

Future research should further investigate interactions between human drivers and highly automated vehicles in mixed traffic. In the short term, (multi-agent) simulator studies and driving studies using a vehicle-in-the-loop can be used to provide further insight into human-machine interactions. However, these simulator or hybrid studies need to be followed by testing in a real-world traffic environment in the long run.

11 References

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Appendix A: Expert interviews

In welchen Fahrumgebungen (z.B. Autobahn, dort bestimmte Streckenabschnitte) werden sich hochautomatisierte Fahrzeuge auf SAE Level 3 finden?

- Ausschließlich Autobahn bzw. autobahnähnliche Strecken mit baulicher Trennung der Fahrstreifen
- Einige Experten sprechen von einer Freigabe nur aus ausgewählten Strecken bzw. auf Streckenabschnitten
- Der Anwendungsfall automatisiert fahrender Pkw in der Stadt ist für die Markteinführung in den nächsten 5 Jahren zunächst nicht relevant.

Sind dies ausschließlich Autobahnen/autobahnähnliche Straßen? Sind alle Autobahnen in allen Abschnitten geeignet (bestimmte Mindestanforderungen; Baustellen; Kreuze, Auf- und Abfahrten, alle Fahrstreifen)?

- Baustellen sind in ihrer Gestaltung (Fahrbahnmarkierungen, Fahrbahnbreite etc.) sehr unterschiedlich, sodass das System Schwierigkeiten haben wird, zuverlässige Vorhersagen zu treffen. Vor allem die Fahrbahnmarkierung ist zunächst eine wichtige Informationsquelle für das automatisierte System. Jedoch ändert sich die Fahrbahnmarkierung über den Verlauf von Baustellenarbeiten. Ebenso können die Markierungen schlecht aufgrund von Verschmutzung schlecht erkennbar, teilweise zerstört, oder gar nicht mehr vorhanden sein. Es wird dementsprechend eine Übergabe an den Fahrer stattfinden.
- Denkbar sind hier jedoch auch Unterscheidungen in verschiedene Versionen der Automatisierung, sodass ein Fahrzeug mit einer Premiumvariante eines automatisierten Systems auch Baustellen automatisiert durchfahren könnte während eine Basisvariante der automatisierten Fahrfunktion an den Fahrer übergeben würde.
- Hochautomatisierte Fahrzeuge werden alle Fahrstreifen benutzen, unter Einhaltung des Rechtsfahrgebots. Auch bei der Benutzung des linken Fahrstreifens soll die zulässige Höchstgeschwindigkeit eingehalten werden.
- Bei Autobahnkreuzen sind die Experten uneinig, da es hierbei auf die Komplexität des Kreuzes ankommt. Es ist möglich, dass ein Level 3 System einfache Abfahrten allein bewältigt, komplexe Spurführungen jedoch nicht. Hierbei ist eine Überlegung, dass es für den Fahrer einfacher ist, die Fahraufgabe zunächst vor allen Autobahnkreuzen zu übernehmen – bis das System alle Autobahnkreuze unabhängig von der Komplexität allein bewältigen kann.
- Auf- und Abfahrten sind Übergabesituationen, welche das hochautomatisierte System mit dem aktuellen Stand der Technik noch nicht selbstständig lösen kann. Ein Experte betonte, dass für den Anwendungsfall des Auf- und Abfahrens noch mehr Erprobung der Fahrfunktion notwendig ist. Ob die Fahrfunktion bei der Markteinführung in der Lage sein wird, diese Situation zu selbstständig zu lösen, hängt von den Ergebnissen der Erprobung ab.

Was ist im Stau, bei Unfällen, mit der Rettungsgasse?

- Stau- und Kolonnenverkehr (bis 60 km/h) sind das Einführungsszenario für hochautomatisierte Systeme auf der Autobahn. Das System sollte in der Lage sein, vorhersehbare Staus selbstständig zu bewältigen. Unklar ist für einige Experten aktuell jedoch, wie das System auf Staubildung reagiert.
- Hochautomatisierte Fahrzeuge müssen in der Lage sein, selbstständig eine Rettungsgasse zu bilden.
- Bei Unfällen, welche von der Polizei abgeschirmt werden, wird das hochautomatisierte Fahrzeug an den Fahrer übergeben.
- Der nächste Schritt ist das freie Fahren auf der Autobahn, hierbei ist eine Höchstgeschwindigkeit von bis zu 130 km/h (Richtgeschwindigkeit) vorgesehen.

In welchem Zeithorizont wird eine Einführung im urbanen Raum absehbar?

- Vermutlich hier auch ein aufbauendes Vorgehen, sodass der Begriff urbaner Raum noch in unterschiedliche Aspekte unterteilt werden muss.
- Denkbar wäre generell eine Einführung in Bereichen mit weniger unterschiedlichen Verkehrsteilnehmern oder auf weniger komplexen Straßensystemen wie etwa Landstraßen, bevor eine Zulassung im urbanen Raum erfolgt.

Wie reagiert das System auf unterschiedliche Wetterbedingungen?

- Übernahmesituation bei durch Regen oder Nebel behinderten Sensor.
- Erkennung von Glätte bisher nicht eindeutig. Bei bevorstehendem Gewitter ebenfalls Übernahme durch Menschen.

Kennzeichnung von automatisierten Fahrzeugen

Wird es für menschliche Autofahrer im Mischverkehr auf den ersten Blick von außen erkennbar sein, dass es sich bei einem Fahrzeug um ein automatisiertes Level 3 Fahrzeug handelt? Wie?

- Auf den ersten Blick ist das hochautomatisierte Fahrzeug auf der Autobahn wahrscheinlich nicht identifizierbar, jedoch zeichnet es sich durch eine stets regelkonforme, vorsichtige Fahrweise aus, welche man so von menschlichen Fahrer nicht gewohnt ist. Das Verhalten könnte schon eine gewisse Form der Kennzeichnung nach außen hin sein.
- Am Verhalten des Fahrzeugführers wird eine Aktivierung des Level 3 Systems ebenso erkennbar sein.

Wird es eine Kennzeichnung für automatisierte Level 3 Fahrzeuge geben (z.B. External HMI durch Lichtanzeige am Fahrzeug)? Wie wird diese aussehen? Wird dies einheitlich für alle Marken sein?

- In der Literatur ist das Thema Kennzeichnung Gegenstand einer aktuellen Diskussion: Einerseits könnte eine Kennzeichnung andere menschliche Fahrer herausfordern und zu riskanten Fahrmanövern animieren, um zu sehen, wie das Fahrzeug beispielweise auf knappes Einscheren reagiert. Andererseits verstärkt zu vorsichtigem Verhalten auffordern, und bei menschlichen Fahrer auch zu Misstrauen gegenüber dem Fahrzeug führen.
- Die Anzahl der Fahrmanöver auf der Autobahn sind longitudinal und lateral begrenzt, sodass einige Experten argumentierten, dass eine Kennzeichnung möglicherweise

nicht sinnvoll ist. Bei einem Spurwechsel gibt es beispielsweise auch den Blinker, der diesen nach außen hin anzeigt. Außerdem sehen Folgefahrer an der Fahrzeugbewegung, dass ein automatisiertes Fahrzeug den Fahrstreifen wechselt. Eine zusätzliche Kennzeichnung könnte hier sogar missverständlich sein.

- Ein Vorteil wäre, dass menschliche Fahrer mit einem besseren mentalen Modell arbeiten können. So können die Verhaltensweisen automatisierter Fahrzeuge besser eingeschätzt werden.
- Die Experten sehen insgesamt keine zwingende Notwendigkeit einer Kennzeichnung für Level 3 Fahrzeuge auf der Autobahn, betonen zum Teil aber, dass eine Untersuchung der Wirkung einer Kennzeichnung auf menschliche Fahrer aufgrund der aktuellen Diskussion sinnvoll ist.
- Es könnte eine Unterscheidung zwischen Nutzung im urbanen Raum und auf der Autobahn denkbar sein. Möglicherweise wäre eine Kennzeichnung jedoch nicht herstellerabhängig, sondern gesetzlich vorgeschrieben. Allerdings sind sich die Experten hier uneinig, in welchem Maße es eine Standardisierung der Außenkennzeichnung geben wird.

Bandbreite menschlichen Verhaltens / Relevante Verkehrssituationen

In diesem Abschnitt geht es darum, inwiefern sich hochautomatisierte Fahrzeuge in bestimmten Situationen möglicherweise anders verhalten als dies menschliche Fahrer tun. Zunächst geht es um das Grundverhalten.
Ist davon auszugehen, dass sich automatisierte Level 3 Fahrzeuge absolut regelkonform verhalten?

- Es ist davon auszugehen, dass gesetzliche Vorgaben eingehalten werden.
- Jedoch können Artefakte entstehen, wenn ein Fahrzeug länger braucht, auf eine bestimme Geschwindigkeit abzubremsen, um den folgenden Verkehr nicht durch Starkbremsungen zu gefährden.

Ganz konkret: Wie genau wird die Geschwindigkeitsbegrenzung eingehalten? Wann beginnt das Fahrzeug, zu verzögern? Wann beschleunigt es wieder? Wie stark beschleunigt und verzögert es?

- Die Geschwindigkeitsbegrenzungen müssen eingehalten werden, sodass das Fahrzeug am Schild die entsprechende Geschwindigkeit fährt. Allerdings kann eine Vollbremsung in Hinblick auf rückwärtigen Verkehr gefährlich sein, sodass hier Rücksicht genommen werden muss und Artefakte entstehen könnten.
- Das Fahrzeug beschleunigt innerhalb der menschlichen Bandbreite bzw. Komfortwerten für longitudinale Beschleunigung. Wenn es erforderlich ist, bremst das Fahrzeug stärker.

Welche Abstände halten hochautomatisierte Fahrzeuge? Wie und wie schnell reagieren sie, wenn der Vorderfahrer bremst oder beschleunigt?

- Ähnliche Abstände wie innerhalb der ACC Grenzen beim nicht-automatisierten Fahren sind denkbar, andererseits müssen gesetzliche Vorgaben eingehalten werden. In späteren Versionen könnte Möglichkeit für den Fahrer bestehen, auf Abstand zu weiteren Fahrzeugen innerhalb des rechtlichen Rahmens Einfluss zu nehmen.

- Ein Experte nennt eine Ziel-Zeitlücke von 2 Sekunden zu vorausfahrenden Fahrzeugen, wobei hier aber auch Bedenken bestehen, dass dann Autos vor dem automatisierten Fahrzeug einscheren, und die Zeitlücke entsprechend verringern.
- Ein weiterer Experte bestätigt diese Aussage und spricht ebenfalls von großen Abständen im Prototypenbereich.

Wie ist die Spurhaltung der hochautomatisierten Fahrzeuge? Fahren diese immer perfekt in der Mitte des Fahrstreifens?

- Es ist möglich, dass die Spurmitte nicht zu jedem Zeitpunkt perfekt gehalten wird, aber der Versatz liegt wahrscheinlich innerhalb der menschlichen Bandbreite.
- Ein dauerhafter Spurversatz könnte den Fahrer des Fahrzeugs irritieren.

Wie steht es um die Vorausschau hochautomatisierter Fahrzeuge? Wird so etwas wie ein Gefahrenpotenzial berechnet, wo dann langsamer gefahren wird?
Denken Sie jetzt bitte über verschiedene Fahrmanöver nach, bei denen hochautomatisierte Fahrzeuge mit menschlichen Fahrern interagieren.
Was sind hier realistische, typische Interaktionen? Wie verhält sich das hochautomatisierte Fahrzeug in dieser Situation? Können Sie das Verhalten der hochautomatisierten Fahrzeuge in diesen Situationen genauer beschreiben? *(Für jede genannte Situation)*

- Überholsituationen
    - ✓ System wird Spurwechsel einleiten, wenn langsameres Fahrzeug rechts fährt, sodass der Überholvorgang stattfinden kann.
    - ✓ Anfangs werden Spurwechsel konservativer durchgeführt werden, sodass lediglich sehr große Lücken genutzt werden. Beim Spurwechsel vertraut das System nicht auf die Kooperationsbereitschaft anderer Fahrzeuge und berechnet wie lange eine Lücke offen sein wird.
- Überholsituation initiiert durch LKW
    - ✓ Antizipationsfunktion des Spurwechselwunsches existiert bereits bei ACC, das System sollte dies ebenfalls mitbekommen.
- Überholenden einscheren lassen
    - ✓ Das System wird eher auf den Fahrspurwechsel und nicht auf den Blinker reagieren, die soziale Situation kann vom System nicht so wahrgenommen und analysiert werden wie von einem menschlichen Fahrer.
- Reißverschlussverfahren
    - ✓ Das System ist hier noch nicht erprobt, sodass es zur Übernahme kommt.
- Drängler/Raser
    - ✓ Sofern möglich, wird das System sich StVO konform an das Rechtsfahrgebot halten. Schert ein anderes Fahrzeug direkt vor dem automatisierten Fahrzeug ein, wird der Sicherheitsabstand langsam aufgebaut.
- Gefahrenwarnung LKW rast in Stauende
    - ✓ System lässt sich nicht aus der Ruhe bringen, allerdings gibt es in einer solchen Situation wenige Ausweichmöglichkeiten. Problematisch könnte hierbei ebenfalls sein, dass das Fahren auf den Standstreifen nicht StVO konform ist, sodass ein Ausweichen des Systems dieser Art unwahrscheinlich ist.

Was macht es möglicherweise anders als menschliche Fahrer?

- Es zeigt stets StVO konformes Verhalten, welches als Bedingung für die Einführung hochautomatisierter Systeme ist (Beispiel: Rechtsfahrgebot und Rettungsgasse)

Sind dabei Interaktionen vorgesehen / geplant?
(Bsp.: Beim Einfädeln blinkt das hochautomatisierte Fahrzeug frühzeitig. Wenn das Fahrzeug auf der Autobahn Lichthupe gibt oder verzögert oder den Fahrstreifen wechselt, wird eingefädelt)

- Von einem frühzeitigen Blinken des Systems wird ausgegangen, allerdings kann eine Lichthupe gemischte Signale senden, sodass von der Nutzung dieser versucht wird, abzusehen.

Ist vorgesehen, dass das Fahrzeug auf ein bestimmtes Verhalten menschlicher Fahrer reagiert?
(Bsp.: Hinterfahrzeug drängelt auf der linken Spur, automatisiertes Fahrzeug bricht Überholmanöver ab und fährt auf die rechte Spur)

- Vermutung der Experten besteht darin, dass ein Drängeln durch Betätigung des Blinkers nicht als StVO-konformes Verhalten zählt und das System daher keinen Algorithmus besitzt, der auf ein solches Drängeln reagiert.

Ist vorgesehen, dass das Fahrzeug aktiv bei menschlichen Fahrern „anfragt“?

- Nein, das ist nicht vorgesehen. Das hochautomatisierte System wird sich zunächst eher reaktiv verhalten.

Hochautomatisierte Fahrzeuge unter sich

Hochautomatisierte Fahrzeuge werden über Kommunikationsmöglichkeiten verfügen. Wird dies auch genutzt werden? Werden sich zwei oder mehr hochautomatisierte Fahrzeuge untereinander abstimmen, z.B. beim Einfädeln, beim Überholen, im Stau?

- Es wird keine direkt Car-2-Car Kommunikation geben, allerdings werden Informationen über die derzeitige Verkehrslage über einen Backend Server an die Fahrzeuge kommuniziert.
- So können beispielsweise Staus vorhergesehen werden.

Führt dies zu einem veränderten Verhalten?
Fahren diese Fahrzeuge möglicherweise in Pulks? Was ist dabei anders als bei menschlichen Gruppen von Fahrzeugen?

- Ein Platooning ist für PKW nicht vorgesehen.

Markenspezifisches

Wird sich ein hochautomatisiertes Fahrzeug von Automobilhersteller A von einem Level 3 von Automobilhersteller B in seiner Fahrweise unterscheiden?

- Im Rahmen Ausgestaltungsmöglichkeiten kann es markenspezifische Unterschiede in der Fahrdynamik (z.B. Beschleunigung & Verzögerung) geben, jedoch müssen diese innerhalb von gesetzlichen Rahmenbedingungen liegen.
- Möglich ist ebenso, dass jeder Hersteller dem Kunden mehrere Fahrzeugtypen bzw. Fahrzeuge mit unterschiedlichen Fahrstilen zur Auswahl stellt.

- ✓ Hierbei wäre denkbar, dass die unterschiedlichen Fahrzeugtypen auch unterschiedliche Situationen autonom meistern.

Übernahmesituationen

Welche Fahrsituationen/Fahrmanöver wird ein hochautomatisiertes Fahrzeug auf der Autobahn zunächst nicht meistern können?

- Fehlende Fahrspurmarkierungen führen wohl, genau wie bereits genannte Wetterbedingungen zur Übernahme durch den menschlichen Fahrer.
- Eine Übernahme geschieht wohl auch bei fehlender baulicher Trennung der gegenläufigen Fahrspuren.
- Hindernisse auf der Fahrbahn und zu geringe Kurvenradien führen zur Übernahme.
- Personen auf der Fahrbahn (sei es in Mautstationen oder Grenzübergängen) führen ebenfalls zur Übernahme.

Wie kann der Fahrer die Übernahme auslösen (z.B. HMI oder Bremsen)?

- Möglich ist die Initiierung der Übernahme von Seiten des Fahrers durch einen dezidierten Knopf oder Hebel, außerdem durch Übersteuern (z.B. Bremsen und/oder Lenken). Es kann zu Unterschieden zwischen Herstellern kommen.

Ist die Gestaltung der Übernahme durch Fahrerverhalten X einheitlich für alle automatisierten Fahrzeuge vorgesehen?

- Bei der Gestaltung der Übernahme kann es markenspezifische Unterschiede geben, z.B. verschiedene Knopfsysteme zur Abschaltung. Das ist eine Herstellerentscheidung.
- Unabhängig vom Hersteller sollte jedoch auch möglich sein, durch Lenken und/oder Bremsen zu übersteuern. Hier könnte das System jedoch verpflichtet sein, noch einmal nachzufragen, ob eine Übernahme tatsächlich erwünscht ist.
- Bei nicht regulärem Wechsel sind Warnblinker und Bremsruck auch für andere Fahrzeuge erkennbar.

Inwieweit wird das Fahrzeug den Fahrer nach der Übernahme weiter unterstützen (z.B. durch Assistenzsysteme)?

- Die Assistenzsysteme (z.B. ACC oder Notbremsassistent) sind nach der Übernahme der Fahraufgabe durch den Fahrer weiterhin aktiv und unterstützen den Fahrer.

Risikominimaler Zustand

Wenn das Fahrzeug an den Fahrer übergeben möchte, weil Systemgrenzen erreicht werden, kann es sein, dass der Fahrer nicht oder nicht schnell genug reagiert. Was werden Fahrzeuge dann tun?

- Das Fahrzeug betätigt den Warnblinker, um die umgebenden Verkehrsteilnehmer zu warnen. Es kommt dann zu einem kontrollierten Stillstand, indem erst das Gas weggenommen wird und dann abgebremst bis zum Stillstand des Fahrzeugs.

Was sind realistische Ausprägungen eines risikominimalen Zustandes auf der Autobahn?

- Es ist denkbar, dass das Fahrzeug auf den Standstreifen fährt oder in der eigenen Fahrspur anhält.

Gibt es dabei besondere Warnungen für die menschlichen Verkehrsteilnehmer?

- Zur Warnung anderer umgebender Verkehrsteilnehmer wird der Warnblinker betätigt.

Appendix B: Supplementary material (Study 1)

Table B1 Multiple pairwise comparison results for the significant factor *target vehicle driving behavior* on all outcome variables examined in Study 1 for scenarios S01 and S02.

		Driving behavior			
	Driving behavior	Automated 1	Automated 2	Human-driven 1	Human-driven 2
Perceived driving mode	Automated 1	-	.472	**< .001**	**<.001**
	Automated 2	.472	-	**.011**	**< .001**
	Human-driven 1	**< .001**	**.011**	-	**.013**
	Human-driven 2	**< .001**	**< .001**	**.013**	-
Perceived safety	Automated 1	-	1.00	.477	**< .001**
	Automated 2	1.00	-	.267	**< .001**
	Human-driven 1	.477	.267	-	**< .001**
	Human-driven 2	**< .001**	**< .001**	**< .001**	-
Comfort	Automated 1	-	1.00	.575	**< .001**
	Automated 2	1.00	-	.106	**< .001**
	Human-driven 1	.575	.106	-	**< .001**
	Human-driven 2	**< .001**	**< .001**	**< .001**	-
Time headway	Automated 1	-	.930	1.00	**< .001**
	Automated 2	.930	-	1.00	**< .001**
	Human-driven 1	1.00	1.00	-	**< .001**
	Human-driven 2	**< .001**	**< .001**	**< .001**	-

***Note.* Significant p-values in bold.**

Table B2 Multiple pairwise comparison results for the significant factor *target vehicle driving behavior* on all outcome variables examined in Study 1 for scenarios S03 and S04.

		Driving behavior			
	Driving behavior	Automated 1	Automated 2	Human-driven 1	Human-driven 2
Perceived driving mode	Automated 1	-	**.010**	**< .001**	**< .001**
	Automated 2	**.010**	-	**.003**	**< .001**
	Human-driven 1	**< .001**	**.003**	-	1.00
	Human-driven 2	**< .001**	**< .001**	1.00	-
Perceived safety	Automated 1	-	1.00	1.00	.088
	Automated 2	1.00	-	1.00	.290
	Human-driven 1	1.00	1.00	-	.910
	Human-driven 2	.088	.290	.910	-
Comfort	Automated 1	-	1.00	.199	.236
	Automated 2	1.00	-	1.00	1.00
	Human-driven 1	.199	1.00	-	1.00
	Human-driven 2	.236	1.00	1.00	-
Time headway	Automated 1	-	1.00	**.006**	**< .001**
	Automated 2	1.00	-	**.003**	**< .001**
	Human-driven 1	**.006**	**.003**	-	.105
	Human-driven 2	**< .001**	**< .001**	.105	-

***Note.* Significant p-values in bold.**

Table B3 Multiple pairwise comparison results for the significant factor *external labelling* on all outcome variables examined in Study 1 for scenarios S01 and S02.

		External labelling		
	External labelling	No labelling	Correct labelling	Incorrect labelling
Perceived driving mode	No labelling	-	1.00	1.00
	Correct labelling	1.00	-	1.00
	Incorrect labelling	1.00	1.00	-
Perceived safety	No labelling	-	1.00	.549
	Correct labelling	1.00	-	1.00
	Incorrect labelling	.549	1.00	-
Comfort	No labelling	-	1.00	1.00
	Correct labelling	1.00	-	1.00
	Incorrect labelling	1.00	1.00	-
Time headway	No labelling	-	1.00	1.00
	Correct labelling	1.00	-	1.00
	Incorrect labelling	1.00	1.00	-

***Note.* Significant p-values in bold.**

Table B4 Multiple pairwise comparison results for the significant factor *external labelling* on all outcome variables examined in Study 1 for scenarios S03 and S04.

		External labelling		
	External labelling	No labelling	Correct labelling	Incorrect labelling
Perceived driving mode	No labelling	-	1.00	.539
	Correct labelling	1.00	-	.182
	Incorrect labelling	.539	.182	-
Perceived safety	No labelling	-	1.00	1.00
	Correct labelling	1.00	-	1.00
	Incorrect labelling	1.00	1.00	-
Comfort	No labelling	-	1.00	1.00
	Correct labelling	1.00	-	1.00
	Incorrect labelling	1.00	1.00	-
Time headway	No labelling	-	1.00	1.00
	Correct labelling	1.00	-	.460
	Incorrect labelling	1.00	.460	-

***Note.* Significant p-values in bold.**

Appendix C: Supplementary material (Study 2)

Table C1 Multiple pairwise comparison results for the significant factor *penetration rate* on the outcome variables (questionnaire data) in Study 2.

		Penetration rate			
	Penetration rate	0%	25%	50%	75%
Perceived safety	0%	-	**< .001**	.077	**.010**
	25%	**< .001**	-	.150	.761
	50%	.077	.150	-	.221
	75%	**.010**	.761	.221	-
Comfort	0%	-	**.028**	**.012**	**.023**
	25%	**.028**	-	.590	.476
	50%	**.012**	.590	-	.694
	75%	**.023**	.476	.694	-
Perceived efficiency	0%	-	**.017**	**.010**	**.005**
	25%	**.017**	-	.724	.230
	50%	**.010**	.724	**-**	.214
	75%	**.005**	.230	.214	-
Perceived penetration rate*	0%	-	.766	.073	**< .001**
	25%	.766	-	**.036**	**< .001**
	50%	.073	**.036**	-	**< .001**
	75%	**< .001**	**< .001**	**< .001**	-
Positive Emotions	0%	-	.595	.659	.559
	25%	.595	-	.913	.893
	50%	.659	.913	-	.839
	75%	.559	.893	.839	-
Negative Emotions	0%	-	.716	.859	.114
	25%	.716	-	.628	.179
	50%	.859	.628	-	.090
	75%	.114	.179	.090	-

***Note.* Significant p-values in bold. **N* = 25.**

Table C2 Multiple pairwise comparison results for the significant factor *external labelling* on the outcome variables (questionnaire data) in Study 2.

		External labelling		
	External labelling	With labelling	Without labelling	Control group
Perceived safety	With labelling	-	.304	.616
	Without labelling	.304	-	.574
	Control group	.616	.574	-
Comfort	With labelling	-	.925	.755
	Without labelling	.925	-	.825
	Control group	.755	.825	-
Perceived efficiency	With labelling	-	.332	.755
	Without labelling	.332	-	.488
	Control group	.755	.488	-
Perceived penetration rate*	With labelling	-	.362	-
	Without labelling	.362	-	-
	Control group	-	-	-
Positive Emotions	With labelling	-	.187	.068
	Without labelling	.187	-	.605
	Control group	.068	.605	-
Negative Emotions	With labelling	-	.471	.261
	Without labelling	.417	-	.755
	Control group	.261	.755	-

***Note.* Significant p-values in bold. **N* = 25, variable was not measured in the control group.**

Table C3 Multiple pairwise comparison results for the significant factor *penetration rate* on the outcome variables (driving data) in Study 2.

			Penetration rate			
		Penetration rate	0%	25%	50%	75%
130 km/h	Average speed	0%	-	**.006**	**.040**	**.008**
		25%	**.006**	-	.968	.108
		50%	**.040**	.968	-	**.045**
		75%	**.008**	.108	**.045**	-
	Mean time headway	0%	-	.507	**.012**	**< .001**
		25%	.507	-	.067	**.001**
		50%	**.012**	.067	-	.172
		75%	**< .001**	**.001**	.172	-
	Minimum time headway	0%	-	.641	.808	.180
		25%	.641	-	.924	**.045**
		50%	.808	.924	-	.167
		75%	.180	**.045**	.167	-
	Percentage of safety-critical interactions	0%	-	.861	**.015**	**.049**
		25%	.861	-	**.005**	**.048**
		50%	**.015**	**.005**	-	.544
		75%	**.049**	**.048**	.544	-
100 km/h	Average speed	0%	-	**.005**	**.004**	**.007**
		25%	**.005**	-	.616	.315
		50%	**.004**	.616	-	.375
		75%	**.007**	.315	.375	-
	Mean time headway	0%	-	.990	.677	.431
		25%	.990	-	.720	.345
		50%	.677	.720	-	.556
		75%	.431	.345	.556	-
	Minimum time headway	0%	-	.063	.963	.413
		25%	.063	-	.088	.312
		50%	.963	.088	-	.319
		75%	.413	.312	.319	-
	Percentage of safety-critical interactions	0%	-	.694	.079	**.024**
		25%	.694	-	.088	.084
		50%	.079	.088	-	.247
		75%	**.024**	.084	.247	-
80 km/h	Average speed	0%	-	.100	**.035**	**< .001**
		25%	.100	-	.493	**.005**
		50%	**.035**	.493	-	**.013**
		75%	**< .001**	**.005**	**.013**	-
	Mean time headway	0%	-	.769	.245	**.003**
		25%	.769	-	**.041**	**< .001**
		50%	.245	**.041**	-	**.015**
		75%	**.003**	**< .001**	**.015**	-
	Minimum time headway	0%	-	.932	.415	**.001**
		25%	.932	-	.168	**< .001**
		50%	.415	.168	-	**.005**
		75%	**.001**	**< .001**	**.005**	-
	Percentage of safety-critical interactions	0%	-	.556	.276	.113
		25%	.556	-	.123	**.047**
		50%	.276	.123	-	.601
		75%	.113	**.047**	.601	-

Note. **Significant p-values in bold.**

Table C4 Multiple pairwise comparison results for the significant factor *external labelling* on the outcome variables (driving data) in Study 2.

			External labelling		
		External labelling	With labelling	Without labelling	Control group
130 km/h	Average speed	With labelling	-	.468	.611
		Without labelling	.468	-	.815
		Control group	.611	.815	-
	Mean time headway	With labelling	-	.735	.525
		Without labelling	.735	-	.342
		Control group	.525	.342	-
	Minimum time headway	With labelling	-	.860	.976
		Without labelling	.860	-	.883
		Control group	.976	.883	-
	Percentage of safety-critical interactions	With labelling	-	.596	.565
		Without labelling	.596	-	.279
		Control group	.565	.279	-
100 km/h	Average speed	With labelling	-	.174	.721
		Without labelling	.174	-	.306
		Control group	.721	.306	-
	Mean time headway	With labelling	-	.164	.844
		Without labelling	.164	-	.237
		Control group	.844	.237	-
	Minimum time headway	With labelling	-	.405	.914
		Without labelling	.405	-	.476
		Control group	.914	.476	-
	Percentage of safety-critical interactions	With labelling	-	.379	.354
		Without labelling	.379	-	.079
		Control group	.354	.079	-
80 km/h	Average speed	With labelling	-	.185	.887
		Without labelling	.185	-	.234
		Control group	.887	.234	-
	Mean time headway	With labelling	-	**.036**	.420
		Without labelling	**.036**	-	.116
		Control group	.420	.116	-
	Minimum time headway	With labelling	-	.057	.371
		Without labelling	.057	-	.217
		Control group	.371	.217	-
	Percentage of safety-critical interactions	With labelling	-	.384	.210
		Without labelling	.384	-	**.040**
		Control group	.210	**.040**	-

***Note.* Significant p-values in bold.**

Appendix D: Supplementary material (Study 3)

Table D1 Multiple pairwise comparison results for the significant factor *lateral offset* on the outcome variables (questionnaire data) in Study 3.

		Lateral offset		
	Lateral offset	Left	None	Right
Perceived risk	Left	-	**< .001**	.087
	None	**< .001**	-	**< .001**
	Right	.087	**< .001**	-
Perceived loss of control	Left	-	**< .001**	.328
	None	**< .001**	**-**	**< .001**
	Right	.328	**< .001**	-
Understandability	Left	-	**< .001**	**.001**
	None	**< .001**	**-**	**< .001**
	Right	**.001**	**< .001**	-
Speed rating	Left	-	.797	.544
	None	.797	-	.057
	Right	.544	.057	-
Lateral distance to the pedestrian	Left	-	**< .001**	**< .001**
	None	**< .001**	-	**< .001**
	Right	**< .001**	**< .001**	-
Lateral distance to the parking stand	Left	-	**< .001**	**< .001**
	None	**< .001**	-	**< .001**
	Right	**< .001**	**< .001**	-
Lateral distance to oncoming traffic	Left	-	**< .001**	**< .001**
	None	**< .001**	-	**< .001**
	Right	**< .001**	**< .001**	-

***Note.* Significant p-values in bold.**

Table D2 Multiple pairwise comparison results for the significant factor *lateral offset* on the outcome variables (questionnaire data; with vs. without deceleration) in Study 3.

		Lateral offset		
	Lateral offset	Left	None	Right
Perceived risk	Left	-	.396	**.001**
	None	.396	-	**.002**
	Right	**.001**	**.002**	-
Perceived loss of control	Left	-	1.00	**< .001**
	None	1.00	**-**	**< .001**
	Right	**< .001**	**< .001**	-
Understandability	Left	-	**.368**	**< .001**
	None	.368	**-**	**.001**
	Right	**< .001**	**.001**	-
Speed rating	Left	-	1.00	.141
	None	1.00	-	.108
	Right	.141	.108	-
Lateral distance to the parking stand	Left	-	.056	**.004**
	None	.056	-	**.044**
	Right	**.004**	**.044**	-

***Note.* Significant p-values in bold.**